Exploring the Influence of Information Overload in the Context of Digital Learning Tools

PhD Thesis

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A thesis submitted for the degree of

Doctor of Philosophy

December 3, 2025

Abstract

The proliferation of digital learning tools in higher education offers flexibility but presents the significant challenge of information overload. This research investigates digital learning tools -induced information overload from an Information Science perspective, examining its multifaceted nature. Despite extensive research, studies often treat information overload as a singular, static construct. This research introduces a novel conceptual framework that reconceptualises information overload as a multidimensional construct within digital learning environments, integrating stress theory and person–environment fit to empirically link overload dimensions to digital fatigue and academic performance.

The research first developed the conceptual framework for information overload, then utilised a quantitative online survey with 200 UK undergraduate students (analysed using structural equation modelling) to test it, and finally involved a qualitative systematic review of 38 articles (analysed using thematic analysis) to identify strategies to deal with information overload.

Key finding from quantitative analysis confirmed specific information overload dimensions (content, social, system features) significantly predict digital fatigue, with content overload being the strongest predictor; communication overload was non-significant. Key digital learning tools characteristics (e.g., volume, irrelevance, excessive interactions, interruptions, complexity) were identified as significant triggers. Digital fatigue negatively impacted perceived academic performance. Unexpectedly, higher technology self-efficacy amplified the positive effect of content overload on digital learning tools. The systematic review identified four strategy categories: personal strategies, organisational and technological, educational and training, and communication and information sharing.

This research contributes to the field of information science by advancing the understanding of information overload as a complex phenomenon by: firstly, conceptualising and empirically testing information overload as a multifaceted construct within on digital learning tools; secondly, advancing theoretical understanding via stress theory integration to empirically demonstrate the pathway from on digital learning tools triggers through overload dimensions to student fatigue and performance; and finally, providing a systematic identification and synthesis of diverse strategies for managing information overload derived from the systematic review. This research provides valuable practical insights for a wide range of stakeholders in higher education, including policymakers, educators, educational technologists, and information literacy specialists, by directly addressing the phenomenon of information overload and its impact on student well-being and academic success within increasingly complex digital learning environments.

Table 1: Abbreviations

Abbreviation	Concept
IS	Information Science
IO	Information Overload
CO	Content Overload
CMO	Communication Overload
SO	Social Overload
SFO	System Features Overload
IV	Information Volume
II	Information Irrelevance
IE	Information Equivocality
HY	Hyperconnectivity
EI	Excessive Interaction
IN	Interruption
PC	Pace of Change
CX	Complexity
DF	Digital Fatigue
PAP	Perceived Academic Performance
TSE	Technology Self-efficacy
SNS	Social networking sites
ODFs	Online discussion forums
LSM	Learning Management Systems

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Acknowledgements

I am grateful to a number of people who helped me to complete this dissertation. First, I would like to thank my supervisors, Dr Yashar Moshfeghi and Prof. Ian Ruthven, for the encouragement and support they provided during this arduous process. There were numerous overwhelming occasions in this process that seemed surmountable after discussions with them. Words cannot express my gratitude towards them. Not only were they wonderful mentors to me, but they also helped me at every stage of the dissertation, including partial funding for the data collection. To my friends for their support, and everyone who agreed to participate in the research, without them, this research would not have been possible. Special thanks to my friend Abdul-Hamid for his support and encouragement.

To my family, my parent who consistently prayed for me and requested Allah to assist me. And to all my sisters and my brothers (Abdalmajid, Monier, Ahmed), I appreciate your encouragement and love. My sincere love and gratitude to my wife and my adorable children (Mohammed, Abdalrahman, and Sirajeddin!) for making this long journey with an absent husband and father. I am grateful for their love, understanding, and continuous support during my study. Lastly, I deeply appreciate the support of the Ministry of Higher Education, Research & in Libya, and the Libyan Cultural Attaché in London for offering me this scholarship and funding my education.

I would also like to appreciate the support from fellow doctoral students, especially Mohammed Binawudaa, with whom I shared my experiences while going through the process. Thanks are also due to my friends who participated in the pretest and pilot study. I would like to take this chance to thank faculty and staff members of the

Department of Computer and Information Science, University of Strathclyde, who helped me see this day today.

Chapter 1

Introduction

1.1 Overview

The exponential growth of the digital landscape has made information globally accessible, ushering in what is commonly termed the 'age of information' (Belabbes et al., 2023). Information overload (IO) has emerged as a critical challenge in this information era, as individuals face an unprecedented volume of information from diverse sources. While concerns about the information overload phenomenon have existed as long as the information itself (Shahrzadi et al., 2024), the rapid advancement of technology, the proliferation of digital platforms, and the expansion of online content creation have intensified this challenge significantly over recent decades (Bawden and Robinson, 2020). This ubiquitous phenomenon has been linked to negative effects such as time loss, decreased efficiency, and reduced well-being (Al Abdullateef et al., 2021; Aussu, 2023; Karr-Wisniewski and Lu, 2010), influencing all levels of society, encompassing areas such as schooling, governance, domestic life, recreation, and our roles as citizens, since the late 20th century (Bawden and Robinson, 2020). This aligns with findings in Information Retrieval research, where cognitive processes such as relevance assessment, satisfaction, and the realisation of information need have been shown to shape how individuals respond to high information volumes McGuire and Moshfeghi (2024); Michalkova et al. (2022, 2024); Moshfeghi et al. (2016); Pinkosova et al. (2020).

1.2 Research Problem

The pervasive issue of IO presents significant challenges within contemporary higher education, particularly exacerbated by the increasing use and reliance on digital learning tools (DLTs). DLTs encompass a wide array of technological resources, applications, and platforms, encompassing institutional learning management systems (LMS), social networking services (SNS), online forums, and instant messaging apps. Such tools are used by students to enhance their learning (Kasim and Khalid, 2016; Zulkanain et al., 2019). While they offer benefits like flexibility and enhanced communication (Savolainen et al., 2018), their proliferation, diverse functionalities, and the sheer volume of information they generate contribute significantly to the cognitive burden experienced by students. Understanding the specific ways DLTs contribute to IO is crucial, yet current studies often treat IO as a singular, static construct, overlooking the dynamic system, multiple information channels, and user engagement patterns inherent in DLT usage (Belabbes et al., 2023).

Investigating IO induced by DLTs from an Information Science (IS) perspective is particularly pertinent. IS provides the theoretical frameworks and methodological approaches necessary to analyse information behaviour, information processing limits, and the design of information systems (Borko, 1968; Saracevic, 2009). This perspective allows for the examination of how students interact with the complex information ecology created by multiple DLTs, moving beyond simply quantifying information volume to understanding the qualitative aspects of information management challenges within digital learning environments.

Furthermore, a critical consequence of sustained IO in the context of DLT engagement is the emergence of 'digital fatigue' (Romero-Rodríguez et al., 2023). Beyond simple tiredness, this type of fatigue manifests as cognitive strain, weariness, reduced motivation, and diminished energy, which are specifically attributed to the use of digital technologies for learning (Menting et al., 2018; Romero-Rodríguez et al., 2023). Digital fatigue can act as a cognitive barrier, impairing information seeking and processing, and ultimately affecting learning outcomes and perceived academic performance (Al Abdullateef et al., 2021; Belabbes et al., 2023; Savolainen et al., 2018).

While the negative impacts of IO have been well documented in recent years, including in the context of widespread online learning and communication during the COVID-19 pandemic from 2020 onwards (Alheneidi et al., 2021; Conrad et al., 2022), research specifically linking DLT-induced IO to digital fatigue and subsequent effects on student well-being and academic performance in the current higher education landscape remains limited. This research aims to address this need by investigating the relationship between IO from DLTs, digital fatigue and perceived academic performance among UK higher education students.

1.3 Motivation

The increasing use of DLTs in higher education, notably accelerated by the COVID-19 pandemic's widespread online learning, has fundamentally reshaped the learning landscape. While these technologies offer numerous benefits, they also introduce significant challenges, particularly the risk of IO among students (Alheneidi et al., 2021; Conrad et al., 2022). This research is driven by the critical need to understand the impact of this pervasive phenomenon across the spectrum of digital learning platforms, extending beyond specific tools such as videoconferencing systems. For instance, prior research conducted during COVID-19 explored behavioural constructs like boredom, escapism, apathy, and IO, empirically examining their relationships with Zoom fatigue phenomenon (Ebardo et al., 2021).

Furthermore, as higher education institutions continue to evolve their pedagogical approaches in the post-COVID-19 era, a sustained reliance on digital learning technologies is anticipated. Therefore, academic inquiry into IO within this evolving context is vital for informing strategies. Such strategies can optimise the use and design of DLTs—aligning them more closely with students' actual information needs—thereby fostering learning outcomes while mitigating potential negative consequences for students.

1.4 Research Quesations

Based on the discussion above, it is clear that while DLTs offer significant benefits, their overuse can lead to IO and digital fatigue, which in turn may undermine academic performance. To address the issues identified in existing research, this study also seeks to explore the specific characteristics of DLTs that contribute to IO and the strategies that can mitigate its negative impacts. Consequently, this research seeks to answer the following research questions:

RQ1: What are the IO dimensions that contribute to digital fatigue?

RQ2: What characteristics of DLTs are associated with each IO dimension?

RQ3: What is the influence of digital fatigue correlated with DLTs use on students' perceived academic performance?

RQ4: What strategies are used to manage or alleviate IO?

1.5 Research Aim and Objectives

The aim of this thesis is to investigate the IO induced by DLTs from an IS perspective and to examine its effects on digital fatigue and higher education students' perceived academic performance in the UK. To answer the specified research questions, this research seeks to achieve the following objectives:

- To develop a conceptual framework for IO within the context of DLTs through literature integration, serving as the foundational theoretical structure underpinning the investigation into RQ1, RQ2, and RQ3.

- To empirically test this conceptual framework model via a questionnaire to address RQ1 (identifying IO dimensions), RQ2 (determining associated DLT characteristics), and RQ3 (assessing the influence of digital fatigue on perceived academic performance).

- To conduct a systematic review of existing literature to determine IO management strategies (thereby answering RQ4).

1.6 Definition of Terms

Digital learning tools refer to various technological resources, applications, and platforms that are utilised by students to facilitate their learning and educational experiences in a digital environment. These tools leverage digital technologies to offer new and innovative ways for students to access educational content, interact with course materials, collaborate with peers, and engage with instructors and learning resources (e.g., email, recorded videos, learning management systems (LMS), collaboration tools, social networking services (SNSs), online forums, and instant messaging apps).

Information overload is a state of cognitive strain triggered by an overwhelming amount of information that surpasses an individual's processing capacity, leading to adverse emotional and cognitive effects (Belabbes et al., 2023).

Content overload refers to the subjective experience of feeling overwhelmed when a student encounters an excessive amount of information that exceeds their capacity to process within the available time and cognitive resources (Eppler and Mengis, 2008; Karr-Wisniewski and Lu, 2010).

Communication overload refers to a situation wherein the demands of multiple channels within DLTs, such as emails and instant messaging, exceed a student's capacity to effectively handle them (Karr-Wisniewski and Lu, 2010).

System features overload arises when the requirements for utilising features within DLTs exceed the students' capacity to manage them effectively (Karr-Wisniewski and Lu, 2010).

Social overload refers to the subjective experience of feeling when the engagement in social interaction within DLTs (e.g., SNS, online forums, group work) exceeds students' interaction ability, resulting in a feeling of being overwhelmed (Maier et al., 2012).

Information irrelevance refers to the degree to which the information available on DLTs is unaligned with a student's specific needs within their digital learning environment

(Guo et al., 2020).

Information equivocality refers to situations where there is a lack of clarity and understanding, leading to uncertainty and difficulties in interpreting information (Grover et al., 2006).

Hyperconnectivity refers to the state of being constantly connected, easily reachable, and immersed in a networked environment that offers abundant information, interactivity, and the capability to record and preserve personal experiences (Fredette et al., 2012)

Interruption is defined as a synchronous interaction that the recipient does not initiate, is unscheduled, and results in the recipient discontinuing their current activity (Rennecker and Godwin, 2005).

Digital fatigue refers to the feeling of exhaustion that arises from prolonged screen exposure. (Romero-Rodríguez et al., 2023).

Excessive interactions refer to the experience of feeling when the level of interaction required from a student exceeds her/his ability to engage and cooperate effectively. This may include activities such as group work, peer interactions on online forums, or other social engagements with friends or peers in virtual networks (Boon, 2016).

Perceived Academic Performance refers to a student's subjective evaluation of their academic achievement, considering their attitudes, abilities, effort, and accomplishments as reflected in their grades (Cruz et al., 2024).

Technology self-efficacy represents the extent to which an individual believes they can effectively use technology to accomplish desired tasks (Gelbrich and Sattler, 2014)

1.7 Thesis outline

This thesis is organised into three main parts, outlined below.

PART I: INTRODUCTION, BACKGROUND, METHODOLOGY, AND CONCEPTUAL FRAMEWORK

- Chapter 1 – Introduction

This chapter sets the stage by presenting the research problem, significance, and motivation. It details the research objectives, key questions, and defines the central concepts (such as DLTs and IO). It also provides an overview of the thesis structure.

- Chapter 2 – Background

This chapter reviews the foundational literature in information science, focusing on the evolution and multifaceted nature of IO. It explores the role of DLTs in higher education, examines the benefits and challenges these tools bring, and discusses the specific issues related to digital fatigue.

- Chapter 3 – Research Methodology

This chapter presents the research methodology, a mixed-methods approach combining a quantitative survey and a qualitative systematic review. It justifies this design and describes each research phase, including conceptual framework development and data analysis, alongside ethical considerations, to ensure that the research questions are coherently answered.

- Chapter 4 – Conceptual Theoretical Framework

This chapter presents the development of the conceptual and theoretical framework. It integrates relevant models and theories to explain the various dimensions of IO, setting the stage for the formulation of hypotheses and offering a visual representation of the framework used to assess the impact of DLTs.

PART II: EMPIRICAL INVESTIGATION, ASSESSING ITS IMPACTS AND EXPLORING INTERVENTIONS OF INFORMATION OVERLOAD

- Chapter 5 – Empirical Framework Testing Findings

This chapter reports the results of the quantitative analysis conducted to test the conceptual framework. It includes descriptive statistics, assessment of the measurement model, evaluation of the structural model, and an analysis of moderating effects (technology self-efficacy).

- Chapter 6 – Strategies for Dealing with Information Overload

This chapter focuses on the qualitative component. Using a systematic review and thematic analysis, it synthesises current strategies and interventions for managing IO.

PART III: DISCUSSION AND CONCLUSION

- Chapter 7 – Discussion

This chapter discusses the findings of the empirical (online questionnaire) and strategies dealing with IO (systematic review findings), placing them within the context of existing literature. It discusses the results of testing the conceptual framework, including the influence of the moderating factor (technology self-efficacy).

- Chapter 8 – Conclusion

The final chapter summarises the key findings, contributions to knowledge, and contributions to the practice of the research. It outlines the study's strengths and limitations, offers recommendations for higher education stakeholders (such as policymakers and lecturers), and suggests directions for future research to further explore the phenomenon of IO in DLTs.

This chapter-by-chapter outline provides a clear roadmap of the thesis, indicating how each section contributes to exploring the impact of DLTs on IO and its subsequent effects on digital fatigue and perceived academic performance.

1.8 Summary of Chapter

This chapter has presented the research motivation, addressed the research problem, and outlined the aim and objectives of the study. Also, defining key conceptual terms. Additionally, it provided a structured overview of the thesis. The next chapter delves into the background of the study context in more detail, situating this original research in relation to existing literature.

Chapter 2

Background

2.1 Introduction

This chapter provides the necessary background to contextualise the research presented in this thesis. It begins by outlining key concepts within IS, the disciplinary perspective adopted herein. The core phenomenon of IO is then explored, detailing its historical origins and conceptual evolution. Finally, the chapter examines the landscape of DLTs in UK higher education, including their prevalent types, benefits, and the specific challenges of IO and the digital fatigue they introduce.

2.2 Information Science

2.2.1 Understanding Information Science

The term *"information science"* refers to the field dedicated to studying the characteristics and behaviour of information and its associated communication systems. It explores how information flows, the forces that influence this flow, and the methods for processing data to maximise its accessibility and usability. The discipline covers the entire lifecycle of information from its creation and collection to its organisation, storage, retrieval, interpretation, conveyance, and utilisation (Borko, 1968). IS is fundamentally shaped by *information behaviour* and *information retrieval.* Information behaviour focuses on the human and social aspects of information use, exploring how individuals and communities seek, access, use, and interact with information. This orientation examines the motivations behind information seeking, the cognitive processes involved, and the broader social factors that influence how information is consumed and shared. On the other hand, information retrieval is more concerned with the technical aspects of organising and retrieving information. This involves the development and refinement of systems, techniques, and technologies collectively referred to as information retrieval. The components of information retrieval systems are designed to ensure that information is efficiently stored, categorised, and made accessible when needed. From its earliest days, IS has worked to bridge and synergise these two orientations, combining an understanding of human information behaviour with the development of advanced systems for effective information retrieval, ensuring that both users' needs and the technical infrastructure required to meet them are adequately addressed (Saracevic, 2009).

2.2.2 Interdisciplinary Nature of Information Science

To solve problems related to information management, IS integrates theories, techniques, and technologies from a wide range of disciplines, including computer science, cognitive science, psychology, mathematics, logic, electronics, and communication, among others (Ibekwe et al., 2019; Paul et al., 2014; Saracevic, 2009). IS seeks to harness multidisciplinary considerations to address issues related to the generation, organisation, representation, processing, distribution, and communication of information, ensuring that it can be accessed and used effectively. In other words, IS encompasses both a theoretical component, which explores the subject purely for understanding, and an applied science component, which focuses on creating practical services and products (Borko, 1968; Saracevic, 2009).

2.2.3 The Role of Information Science in Practice

In practice, IS focuses on the effective collection, storage, retrieval, and use of information. Its scope involves managing recordable knowledge and information through the application of various technologies and services. As both a professional practice and a scientific field, IS aims to improve the communication of knowledge, ensuring that it is accessible and valuable for individuals, organisations, and society. The primary focus is on handling recorded human knowledge—particularly its representation, organisation, and retrieval—rather than just knowing the information itself (Ibekwe et al., 2019; Saracevic, 2009).

In today's rapidly evolving digital landscape, information science plays an increasingly vital role. Individuals live in an era marked by an unprecedented influx of information production, which presents both opportunities and challenges (Saracevic, 2009). *Information overload* has emerged as a significant challenge in the digital landscape, intensifying as the sheer volume of information potentially overwhelms individuals. The phenomenon of IO has persisted for eras (Shahrzadi et al., 2024). However, the digital landscape has accelerated this issue even further in the late second decade of the twentieth century (Bawden and Robinson, 2020). Thus, IS plays a crucial role in addressing such issues and employing approaches, such as recommendation systems (Jian et al., 2022) and filtering (Jia and Wang, 2021; Savolainen, 2007) digital systems. By understanding user preferences, behaviours, and needs, these systems can deliver tailored information, presenting content that is specifically relevant to each user's context (e.g. Huang et al., 2024; Kang and Chung, 2022; Lin et al., 2022; Saracevic, 2009). This selective approach reduces the overwhelming nature of information-rich environments by narrowing the data set that users need to engage with. This chapter offers a concise introduction to IO. Relevant literature is integrated to develop a theoretical understanding of IO, building on existing research and model development in the subsequent chapters. The following section begins by explaining the conceptualisation of IO. Similar patterns are visible in neuro-information retrieval research, where users' relevance judgements and satisfaction levels have been shown to correlate with cognitive processing demands during high-load information tasks **??**.

2.3 Information Overload

2.3.1 The Origins of Information Overload

The concept of *information overload* has developed significantly over the years, with notable contributions from various scholars. Although the term was not explicitly coined until recent years, the concept of IO can be discerned in the late 19th century, as identified by the German sociologist George Simmel (Bawden and Robinson, 2020). Historical concerns about exposure to excessive information date back to ancient and classical times, and early *de facto* solutions to such problems were summaries and lists (indeed, the development of writing itself can be seen as a solution to reduce the IO entailed by memorising information). During the medieval period, the mass transcription and translation of ancient works and contemporary commentaries increased the volume of literary production, and the problem of IO became more acute among literate and learned segments of society. This led to the creation of reference works and organised texts for specific fields (Savolainen, 2007).

The early modern era, marked by the advent of printing, greatly intensified the issue (Bawden and Robinson, 2020), resulting in an ”information explosion” in the 16th and 17th centuries (Rosenberg, 2003). This period saw the introduction of methods like skim reading, indexing, and structured documentation to cope with the growing volume of texts being produced and read (Blair, 2010). By the 18th century, advancements such as encyclopedias, dictionaries, and systematic documentation practices further sought to address the problem (Yeo, 2003).

The 19th-century communications revolution, driven by the rise of newspapers, magazines, and advances in printing technology, marked the beginning of modern awareness of IO (Sarabadani et al., 2018). In the previous century, Diderot (d. 1784) had predicted that as the number of books increased, including organised encyclopedias, etc. designed to mitigate IO, accessing relevant information would paradoxically become as challenging as studying the vast universe (Belabbes et al., 2023). In the late 19th century, Beard highlighted the growing impact of expanding information channels, particularly through the press and telegraph, and was one of the first to recognise the effects of information overload, identifying fatigue and concern as its key consequences (Beard, 1881). The early 20th century introduced bibliographic control tools and the documentation movement Csiszar (2013).

Complaints about overload in scientific research became prominent around mid-century, coinciding with growing awareness of potential solutions offered by emerging computer technologies (which had been successfully developed and used during WWII). In this milieu, the 1948 Royal Society Conference played a significant role in shaping the structure of academic and professional information services at the onset of the digital era. The conference expressed heightened fear that scholars were becoming overwhelmed by the ever-growing volume of information and expressed concern that they could no longer manage the vast influx of potentially relevant material being produced, as continuous streams of new literature filled libraries without pause (Bawden and Robinson, 2020). In his 1945 work, Vannevar Bush proposed the development of a machine called the "memex" to address the growing issue of IO, which had become evident by the end of World War II due to rapid scientific advancements. The memex was envisioned as a system to help individuals organise and access books and documents, effectively serving as the first conceptualisation of an information retrieval system. Bush's primary concern was the overwhelming volume of information available, which made it increasingly difficult for individuals to manage and use effectively Bush (1945).

As scientific advancements continued into the mid-20th century, Alvin Toffler's analysis in *Future Shock* highlighted the accelerating pace of IO driven by modern technologies. This phenomenon was seen as a significant stressor, causing individuals to experience confusion, anxiety, and difficulty in making informed decisions. Toffler's work underscored the profound implications of this overload on human well-being, suggesting that the accelerating rate of change in modern society necessitated new strategies for managing and coping with the influx of information (Toffler, 1970).

The studies by Bawden and Robinson (2020) and Belabbes et al. (2023) significantly advanced the understanding of the detrimental effects of IO. Their research helped bring

IO to widespread attention, where it remained a significant concern throughout the early years of the millennium. They discovered that individuals exposed to excessive information often experience cognitive overload, leading to difficulties in concentration, information processing, and decision-making. Moreover, they noted the emotional consequences of IO, such as anxiety, stress, and frustration. Both studies underscore the negative impacts of IO on individuals, emphasising the challenges it poses for effective decision-making, productivity, and well-being.

2.3.2 The Conceptualisation of Information Overload

IO has become a prevalent and ongoing issue, largely fueled by the information age's unprecedented production and access to information (Shahrzadi et al., 2024). IO is a concept studied across various disciplines, including social sciences (Gross, 1964), management (Eppler and Mengis, 2008), and psychology (Misra and Stokols, 2012). Within the field of IS, IO is regarded as a central concept, as a comprehensive understanding of how users manage, filter, and process information is fundamental to IS research (Bawden and Robinson, 2020; Belabbes et al., 2023; Graf and Antoni, 2021).

IO was initially perceived to be primarily an issue of excessive quantity, as when the term 'information overload' was first coined in 1964 by Gross (1964), who defined it as the point at which the volume of information surpasses a system's ability to process it efficiently. He highlighted the limitations of human cognitive capacity in managing large quantities of information (Gross, 1964). Similarly, a more recent definition by Eppler and Mengis (2008) considers IO from a management perspective as the stress that occurs when the volume of information exceeds an individual's ability to process it. This leads to impaired decision-making, confusion for the user, and negative impact on their overall performance (Alheneidi et al., 2021). On the other hand, a widely cited definition from the IS discipline, offered by Bawden and Robinson Bawden and Robinson (2020), describes IO as a situation in which an abundance of relevant and potentially useful information becomes more of an obstacle than a benefit.

IO today encompasses far more than just the sheer volume of available information

(Belabbes et al., 2023). Despite its importance, there remains no universally accepted definition, as researchers have yet to reach consensus on a clear, singular understanding of the term and conceptualise it from different disciplinary perspectives (Aussu, 2023; Belabbes et al., 2023). Subsequently, Belabbes et al. (2023), in their state-of-the-art work, aimed to provide a conceptual analysis of IO within the field of IS using Rodgers' approach to concept analysis, a systematic methodology developed initially in nursing science to grasp and refine concepts (Foley and Davis, 2017). They defined IO as a state of cognitive strain triggered by an overwhelming amount of information that surpasses an individual's processing capacity, leading to adverse emotional and cognitive effects (Belabbes et al., 2023).

In addition to the lack of a unified definition of IO, the phenomenon has been labelled with various interchangeable terms, such as 'communication overload' Bawden and Robinson (2020), 'social overload'(Eppler and Mengis, 2008), and 'cognitive overload' (Belabbes et al., 2023). The diversity of terms related to IO indicates that the most effective path forward may be to adopt a new approach. This research proposes that IO must be recognised as an inherently multidimensional construct, encompassing a range of different manifestations (for dimensions of IO, see Chapter 4).

Belabbes et al. (2023) highlighted that the consequences of IO can be substantial, potentially eliciting emotional responses that contribute to digital fatigue in individuals (Romero-Rodríguez et al., 2023). Fatigue is typically characterised by psychological and physiological symptoms, including sensations of weariness and diminished energy (Menting et al., 2018). These symptoms subsequently establish or exacerbate cognitive barriers that impede, restrict, or obstruct the information-seeking process, thereby adversely affecting learning outcomes (Belabbes et al., 2023; Savolainen et al., 2018).

Research has documented the negative impacts of IO on students in educational settings, leading to outcomes such as fatigue, burnout, and significant declines in academic performance both prior to the COVID-19 pandemic (Cao and Sun, 2018; Karr-Wisniewski and Lu, 2010; Lee et al., 2016a; Yu et al., 2019; Zhang et al., 2016) and during its peak (Al Abdullateef et al., 2021; Alvarez-Risco et al., 2021; Conrad et al., 2022; Laato et al., 2020). However, there is a notable insufficiency in research concerning the effects of IO on students, post-COVID-19, especially concerning DLTs. Moreover, research remains limited as students face growing exposure to various digital platforms that may contribute to IO, affecting their digital fatigue and perceived academic performance.

2.4 Digital Learning Tools in Higher Education in the UK

DLTs have become integral to the evolving landscape of higher education, marking a significant shift in teaching and learning practices. Recent research highlights that institutions are embedding these tools into core pedagogical processes, not merely for convenience but as part of a broader transformation toward engagement, collaboration, and personalised learning experiences (Muhuri and Mukhopadhyay, 2022). A diverse ecosystem of digital platforms supports this transformation. Learning Management Systems, such as Moodle and Blackboard, provide structured environments for course delivery, assignments, and discussion forums. Social Networking Services, including Facebook, Twitter, and LinkedIn, facilitate informal learning, community building, and professional networking. Additionally, instant messaging applications like WhatsApp enable real-time communication, supporting project coordination and collaborative discussions.

In the UK, the importance of digital learning in higher education surged in 2020, according to a report (Jisc and Emerge Education, 2020). Clark (2023) argues that digital education is now a cornerstone for skill development and academic success, a view that is reinforced by industry data. While the digital learning industry experienced a remarkable 72% increase in 2020 (Department for Business and Trade, 2024), Jisc's latest report for 2023/2024 confirms that this positive trend has been sustained. The report shows that higher education institutions have continued to make year-on-year improvements in key areas of the student digital experience, with student ratings for the quality of digital learning on their courses increasing to 83% and support for effective learning using technology rated at 73% as "above average" (Jisc, 2023). As higher educational institutions continue to invest in digital infrastructure and develop innovative digital curricula, these tools are increasingly central to facilitating both synchronous and asynchronous learning. The evolution of digital learning tools has expanded access to educational resources and paved the way for more collaborative and interactive learning environments. With ongoing technological advancements, digital learning tools are set to play an even more prominent role in shaping the future of higher education in the UK and beyond. Therefore, the pervasiveness and growing importance of DLTs within UK higher education underscore the necessity of studying their potential downsides, such as information overload, making this context particularly suitable for the present research

2.5 Digital Learning Tools

In higher education, student use of DLTs has increased markedly, reflecting broader technological advancements and the demands of 21st-century learning (Kasim and Khalid, 2016). This capability enables students and educators to interact and share resources from any location, creating an accessible and dynamic learning environment. The option for asynchronous communication further enhances learning flexibility, allowing students to engage with content and collaborate with peers at their own pace (Savolainen et al., 2018).

In brief, this study defines DLTs as technological resources, applications, or platforms students use to enhance their learning in a digital environment. They include both officially recommended tools endorsed by educational institutions, as well as any other digital tools that students choose to incorporate into their learning process, such as learning management systems, social networking services, online forums, instant messaging apps, and various other digital platforms.

2.5.1 Social network sites

Social networking sites (SNS) have gained widespread recognition as powerful tools in learning environments (Zulkanain et al., 2019). Their global reach and versatile functionalities make them an essential part of modern education. By enabling seamless communication and fostering engagement, SNS contribute significantly to the learning process (Williams, 2022).

2.5.2 Benefits of SNS for Learning Purpose

Facebook, X, YouTube, and WhatsApp are widely used in educational settings to support learning, as identified in a systematic review by Zulkanain et al. (2019). These platforms serve five key functions: communication, collaboration, information sharing, enhancing learning, and social connection (Zulkanain et al., 2019).

- Communication: SNS enable interaction among students and instructors, facilitating discussions, messaging, and announcements. Facebook and WhatsApp are particularly effective for instant communication. Studies show that Facebook and X are user-friendly and provide communication and interaction, with Facebook's features enriching group discussions (Dafoulas and Shokri, 2016; El Bialy and Ayoub, 2017). However, YouTube is primarily a platform for sharing video content; some studies suggest that its use for direct communication is less common (Zulkanain et al., 2019). For instance, Saw et al. (2013) observed that students predominantly use YouTube as a source for supplementary learning materials rather than for communication.

- Collaboration: Platforms like Facebook, WhatsApp, and X support group work, file sharing, and threaded discussions, enhancing teamwork and peer learning. YouTube is less effective for collaboration. A study by Khatoon et al. (2015) showed that Facebook and WhatsApp can help groups work together more efficiently by allowing them to share files and information directly (Khatoon et al., 2015). These tools encourage teamwork and peer learning by supporting shared documents and project updates.

- Information Sharing: Students use SNS to exchange knowledge and resources. Facebook and WhatsApp allow sharing of files, links, and media; YouTube provides access to educational videos; Twitter enables rapid dissemination through retweets (Zulkanain et al., 2019). Dafoulas and Shokri (2016) found that students utilise Facebook's features, such as sharing videos, photos, and website links, to share knowledge and learn from one another.

- Enhancing Learning: SNS use can improve academic performance, engagement, and critical thinking. Research indicates that SNS usage for learning purposes can enhance academic performance by fostering active learning, engagement, and collaboration—for example, systematic reviews demonstrate their positive impact on learning outcomes (Cavus et al., 2021), and studies on WhatsApp show measurable improvements in students' knowledge and grades (Khan et al., 2017). Although research on X's ability to enhance learning is limited, a few studies (Chawinga, 2017) indicate that the platform can be used to foster critical thinking. This is achieved by allowing students to share and develop ideas through the exchange of thoughts and resources (Zulkanain et al., 2019).

- Social Connection: SNS promote engagement and social presence, helping students build relationships with peers and instructors (Zulkanain et al., 2019). Mansour (2015) showed that platforms such as Facebook, X, and YouTube facilitate student–teacher interactions, thereby strengthening engagement. This interaction further enables students to build stronger peer relationships and collaborate more effectively. Participation in social activities through these platforms also enhances social skills and fosters a stronger sense of social presence within the learning environment (Zulkanain et al., 2019).

Overall, SNS platforms provide multifaceted support for learning, combining communication, collaboration, information access, learning enhancement, and social engagement, though their effectiveness varies by platform and function.

Many educational institutions, including universities in the UK, have recognised the potential of SNS to expand the boundaries of traditional learning. By incorporating these platforms into their academic programs, higher education institutions in the UK have observed how SNS can enhance student performance and enrich the overall academic experience (Williams, 2022).

2.5.3 Rationale for Treating Social Media as Digital Learning Tools

Although social media platforms were not initially designed for formal education, their systematic incorporation into students' day-to-day academic practices makes them integral to the contemporary digital learning ecology in higher education. Empirical work shows that SNS underpin communication, collaboration, information sharing, learning enhancement, and social presence in university contexts (Al Abdullateef et al., 2021; Cavus et al., 2021; Williams, 2022; Zulkanain et al., 2019). Students coordinate group projects, crowdsource explanations, share artefacts, and sustain communities of practice across courses through Facebook groups, WhatsApp, X, and YouTube, blurring the boundary between formal and informal learning (Kasim and Khalid, 2016; Savolainen et al., 2018). In the UK, in particular, continued improvements in students' digital experiences and access to institutional platforms further normalise the use of these tools alongside LMS-based activity (Jisc, 2023).

Conceptually, excluding SNS from the present study would omit a sizeable and pedagogically consequential portion of the actual tools students use to achieve learning goals—precisely the study's definition of DLTs (see Section 2.5). Methodologically, omission would risk under-estimating both the prevalence and the effects of overload stressors that are unique or amplified in SNS spaces, such as *social overload* from persistent social demands (Maier et al., 2012, 2015b), *content overload* from the rapid circulation of mixed-quality resources (Chen et al., 2011; Lee et al., 2016a), and the presence of *ambient, non-course information* that elevates perceived irrelevance (Bawden and Robinson, 2020; Zulkanain et al., 2019). Including SNS, therefore, ensures ecological validity and allows the study to identify triggers, stressors, and strains (e.g., excessive interactions, information irrelevance, social overload; see Chapter 4) that would remain obscured if analysis were limited to institutionally mandated systems alone (e.g., LMS). In short, treating SNS as DLTs is both theoretically warranted and empirically necessary to capture how students actually learn in digitally rich environments.

At the same time, SNS embed ambient information streams that are not strictly related to learning activities, posing risks of distraction and measurement confounds. This study addresses these complexities in two ways. First, by conceptually foregrounding factors such as *information irrelevance* and *excessive interactions* as explicit triggers (Section 4.6.1) and *social overload* as a stressor (Section 4.6.6), the framework does not treat these phenomena as noise but as central mechanisms through which overload emerges in real student practice (Lee et al., 2016a; Xiao and Mou, 2019). Second, the methodological operationalisation in Chapter 3 constrains the analytic lens to *learning-purposed* uses of SNS and makes this scope explicit to participants during recruitment and response (see Section 3.8.4).

2.5.4 Online Discussion Forums

Online discussion forums (ODFs) are widely used in higher education as asynchronous communication tools that enhance the learning experience by supporting activities such as critical reflections, assignments, and peer-to-peer interactions. These forums play a crucial role in facilitating interaction between students and lecturers, making it easier to share information and transfer tacit knowledge. Tutors also frequently engage in these forums, particularly in large classes, to manage collaboration and encourage active student participation (Mokoena, 2013).

ODFs offer several advantages in educational settings. They provide increased opportunities for student involvement, especially for those who may feel hesitant or inhibited in traditional classroom discussions. The asynchronous nature of ODFs allows students to engage at their own pace, promoting more thoughtful responses and encouraging deeper critical thinking (Durairaj and Umar, 2015). Models like Perkins and Murphy's framework even assess the level of critical engagement in these online discussions. Additionally, ODFs foster peer learning by allowing students to exchange ideas, opinions, and insights on various topics (Da Silva et al., 2019).

The interactive nature of ODFs is one of their key strengths. These forums often stimulate discussions through thought-provoking questions that prompt students to reflect on and respond to one another's contributions (Roper, 2007). Depending on the course structure, participation in ODFs may be mandatory or optional, and they can serve multiple purposes, including assignments, structured debates, and collaborative learning exercises. This flexibility allows ODFs to accommodate different learning objectives while fostering greater engagement among students (Mokoena, 2013).

2.5.5 Learning Management Systems

Learning management systems (LMS) play a vital role in digital learning environments, particularly in higher education. LMS platforms, such as Moodle, Blackboard, and ATutor, are web-based software applications designed to manage educational content, student interactions, assessments, and learning progress. These systems offer features like asynchronous and synchronous communication, document sharing, assignment submissions, quizzes, and performance tracking (Kasim and Khalid, 2016).

LMS platforms provide flexibility, accessibility, and ease of use, which are key characteristics for enhancing the learning experience. They enable both students and instructors to engage with content anytime and anywhere, fostering continuous learning. In higher education, LMS is often integrated with other digital tools such as content management systems (CMS) and mobile learning applications, further expanding its utility. Additionally, LMS tools like discussion forums, quizzes, and document management systems enhance student participation, collaborative learning, and overall academic performance (Kasim and Khalid, 2016; Khalid et al., 2015).

2.5.6 Advantages and Disadvantages of Digital Learning Tools

DLTs offer significant benefits to students, particularly in terms of flexibility and communication. DLTs, such as LMS and SNS, enable users to communicate and share resources without the constraints of time or location. These tools allow the exchange of text, images, videos, and documents, creating a dynamic and accessible learning environment. The option for asynchronous communication further enhances flexibility, as students can engage with content and collaborate with peers at their own pace, which is crucial in a fast-paced, digital world (Savolainen et al., 2018). In addition to facilitating communication, DLTs, especially SNS, have become powerful tools for enhancing student engagement. Platforms like Facebook, WhatsApp, LinkedIn, and YouTube enable seamless interaction, fostering a more interactive and collaborative learning experience. These tools help students work together on projects, share files, and exchange insights, promoting teamwork and peer learning. The integration of multimedia content and real-time communication on these platforms also accommodates different learning styles, making education more personalised and engaging (Dafoulas and Shokri, 2016; Zulkanain et al., 2019). Moreover, online discussion forums (ODFs) allow for deeper critical reflection. The asynchronous nature of these forums encourages students to take the time to think through their responses, resulting in more thoughtful contributions and promoting higher-level thinking (Durairaj and Umar, 2015).

Another important benefit of DLTs is their ability to foster a sense of community among learners. SNS platforms, in particular, allow students to interact beyond the confines of the classroom, creating informal spaces for networking and engagement. This sense of connection is particularly valuable in online and distance learning environments, where students may otherwise feel isolated (Zulkanain et al., 2019). Additionally, DLTs provide comprehensive learning management through platforms like Moodle and Blackboard, which organise educational content, assessments, and student interactions. These systems enhance the learning experience by offering structured features such as quizzes, forums, and progress tracking, benefiting both students and instructors (Kasim and Khalid, 2016).

Despite the numerous advantages DLTs offer, their use also brings certain challenges, and one of the most significant issues is IO. The sheer volume of content and communication generated through these tools can overwhelm students, making it difficult to process and synthesise information effectively. This cognitive overload can hinder learning and lead to frustration, particularly when students face fragmented discussions and an abundance of resources (Chen, 2003; Conrad et al., 2022). In addition to the issue of IO, students have highlighted other challenges within digital learning environments. These include delays caused by asynchronous communication, difficulty keeping up with ongoing discussions, and the absence of visual and auditory cues, which can hinder meaningful interaction. For instance, studies have indicated that students experiencing information overload in online learning often struggle to engage in online discussions (Chen et al., 2012). Moreover, concerns have been raised about the inconvenience of access at times and the health risks associated with prolonged screen use, such as strain and exposure fatigue. Chen et al. (2011) noted that fragmented discussions, combined with the high volume of information, greatly contribute to IO (Chen et al., 2011). Similar patterns have been observed in information science and information retrieval, where information overload is conceptualised as a multifaceted phenomenon involving cognitive, emotional, and contextual factors that shape how people experience and manage high volumes of information(Belabbes et al., 2023; Moshfeghi and Pollick, 2019).

2.6 Challenges of Digital Learning Tools: Information Overload and Digital Fatigue

In today's educational landscape, the widespread use of DLTs such as LMS, SNS, and online discussion forums has created new challenges for students. These platforms undoubtedly offer convenient access to information and support ongoing communication, allowing students to participate in collaborative learning and share knowledge effectively. However, this can lead to over-reliance on these tools, which can result in negative outcomes, including suffering from IO (Al Abdullateef et al., 2021; Lee et al., 2016a). Researchers have started investigating the downsides of DLTs. For instance, studies discovered that DLT use contributes to IO (Brooks, 2015; Chen et al., 2011; Delpechitre et al., 2019; Yu et al., 2018).

As students interact with these platforms, they are often confronted with excessive amounts of information, frequent notifications, and complex system interfaces. This overwhelming exposure surpasses their ability to process information efficiently, leading to cognitive strain.

As demonstrated in previous studies, IO manifests in various forms, such as content overload from an abundance of learning materials, communication overload from constant digital interactions, and the difficulty of navigating complex systems. These manifestations of IO are closely linked to digital fatigue, a condition where students experience mental and emotional exhaustion from prolonged digital engagement (Cao and Sun, 2018; Fu et al., 2020; Lee et al., 2016a; Zhang et al., 2022a). Digital fatigue diminishes students' ability to concentrate and negatively affects their academic performance (Al Abdullateef et al., 2021; Yu et al., 2019). As a result, the very tools designed to enhance learning can contribute to a decline in student performance, driven by the overwhelming cognitive demands they impose. The subsequent chapter describes the research methodology and approaches adopted for this research.

2.7 Chapter Summary

This chapter explored the interdisciplinary foundations of IS and its critical role in addressing IO. It reviewed key literature on the use of DLTs in educational contexts and their influence on student learning outcomes. The chapter also traced the historical development of IO, from early concerns about managing large volumes of information to the complex challenges introduced by digital technologies today. Emphasis was placed on the adverse effects of IO, such as digital fatigue and impaired performance.

Chapter 3

Research Methodology

3.1 Introduction

This chapter presents the mixed-methods approach adopted in this thesis, providing the rationale for the chosen methods and describing the procedures for data collection tool development, sampling, recruitment, data analysis, and ethical considerations.

This research aims to answer the research questions identified in Chapter 1:

RQ1: What are the IO dimensions that contribute to digital fatigue?

RQ2: What characteristics of DLTs are associated with each IO dimension?

RQ3: What is the influence of digital fatigue correlated with DLTs use on students' perceived academic performance?

RQ4: What strategies are used to manage or alleviate IO?

The research addresses these questions through the following objectives:

- **Objective 1:** To develop a conceptual framework for IO within the context of DLTs through literature integration, serving as the foundational theoretical structure underpinning the investigation into RQ1, RQ2, and RQ3.

- **Objective 2:** To empirically test this conceptual framework model via a questionnaire to address RQ1 (identifying IO dimensions), RQ2 (determining associated DLT characteristics), and RQ3 (assessing the influence of digital fatigue on perceived academic performance).

- **Objective 3:** To conduct a systematic review of existing literature to determine IO management strategies (thereby answering RQ4).

3.2 Anchoring in Prior Studies

This thesis builds directly on prior studies that conceptualise technology-induced overload and its consequences. Karr-Wisniewski and Lu (2010) distinguished information, communication, and system-feature overload as core stressors arising from technology use. (Lee et al., 2016a) adapted this perspective to SNS and, drawing on the Person–Environment fit and transactional stress views, linked these overload stressors to user fatigue. Subsequent work in academic contexts further connected overload-induced strain (e.g., technostress, exhaustion) to learning outcomes and perceived academic performance (Al Abdullateef et al., 2021; Shi et al., 2020; Yu et al., 2019). Building on these foundations, the present study (i) reconceptualises overload as a multidimensional construct across DLTs used by students, including LMS, forums, and SNS; (ii) integrates stress theory to model pathways from DLT characteristics (triggers) to overload (stressors), to digital fatigue (strain), and finally to perceived academic performance (outcome); and (iii) complements the quantitative model test with a qualitative systematic review to synthesise actionable strategies for mitigating overload in higher education.

3.3 Research Approaches

The choice of research approach hinges on the nature of the research question and the problem being investigated. The 'Research Onion Framework' highlights two primary research approaches: deductive and inductive (Saunders et al., 2019).

In a deductive approach, the research begins with an existing theory or hypothesis. Researchers form hypotheses based on the theory, which are then tested through empirical data collection (Creswell and Creswell, 2023). This approach seeks to confirm or refute the initial hypothesis by examining measurable outcomes. It is particularly suited to quantitative research, where data can be used to test the validity of theoretical proposi-

tions. Deductive research is structured, with a linear path from theory to data, making it ideal for studies with clear expectations or predictions to be validated through objective evidence (Saunders et al., 2019).
Conversely, the inductive approach begins with data and observations, from which theories or explanations emerge. Researchers employing this approach look for patterns, themes, or relationships within the data to build a conceptual framework or theory (Creswell and Creswell, 2017). While inductive research is often associated with exploratory studies—particularly in fields where limited prior knowledge exists—it is not exclusively so. Exploratory research is generally undertaken when a topic is not well understood, and the aim is to gain deeper insights rather than to test existing theories. Inductive approaches support this by allowing patterns to emerge from the data without the constraints of predefined hypotheses (Easterby-Smith et al., 2021).
Generally, the two research approaches differ in their theoretical focus: deductive approaches involve testing established hypotheses to enhance understanding and interpretation of social phenomena; and inductive approaches focus on developing new theories based on observed patterns and insights. Table 3.1 provides a summary of these differences, illustrating how deductive methods contribute to theory validation through empirical testing, whereas inductive methods facilitate theory development from data-driven observations and emerging themes (Saunders et al., 2019).

This study employed both deductive and inductive research approaches to address its objectives. The deductive approach was utilised to test the hypotheses developed within the conceptual framework (see Chapter 4). These were examined using quantitative data gathered through a questionnaire presented in Chapter 5. Conversely, the inductive approach was employed to explore strategies for dealing with IO, focusing on generating new insights through qualitative data from a systematic review. The thematic analysis was used to identify recurring patterns and emerging themes within this data (see Chapter 6). By integrating both approaches, the study accrued the advantages of theory validation and theory generation, ensuring a robust examination of the phenomenon.

Table 3.1: Comparison of Deductive and Inductive Approaches (Saunders et al., 2019)

Feature	**Deductive**	**Inductive**
Logic	Top-down: General to specific	Bottom-up: Specific to general
Certainty	High certainty (if premises are true, the conclusion must be true)	Lower certainty (probabilistic; conclusions may be false)
Theory	Tests existing theories or derives specific predictions	Develops new theories based on observations
Data	Uses existing theories or established facts	Relies heavily on empirical data to form patterns
Approach	Hypothesis testing	Theory building
Advantages	Increased efficiency with a higher likelihood of validating the theory	Greater flexibility with a stronger potential to uncover new insights
Disadvantages	Finding a relevant theory can be challenging, and it may not account for all aspects of the data	It can be time-intensive and harder to communicate effectively

3.4 Research Design

This study adopted a mixed-methods approach, addressing the research questions by integrating quantitative and qualitative methods, as elaborated upon in subsequent sections. The research developed a model for IO within the context of DLTs. An online questionnaire was employed to test the model as part of the quantitative component, while a systematic review, incorporating thematic analysis, constituted the qualitative component. This methodology is widely recognised as a suitable choice for IS research, as noted by Granikov et al. (2020).

3.4.1 The Rationale for Using a Mixed-Methods Approach

A methodological review found that 373 out of 417 IS studies (approximately 89%) utilised mixed methods, highlighting the growing trend of combining quantitative and qualitative approaches (Granikov et al., 2020), which has become increasingly prevalent in the field of IS. Moreover, mixed-methods research is commonly used for validation, and to provide a broader view by integrating findings from different methods, leading to a deeper understanding of the research (Creswell and Creswell, 2023).

Doyle et al. (2016) further elaborated on the justifications for mixed-method research, which were initially outlined by Bryman (2006), to discern seven primary rationales for (i.e., benefits of) conducting mixed-methods research, as outlined below Table 3.3. Moreover, Creswell and Creswell (2023) explains that mixed-methods research is a powerful tool for answering different research questions that demand a more comprehensive approach than either quantitative or qualitative methods alone, offering a richer set of tools to meet the research objectives.

Given these advantages, I selected the mixed-methods approach as the optimal way to address the different research questions in this study. Quantitative survey method is used to explore RQ1, RQ2, and RQ3, which focus on identifying types of IO contributing to digital fatigue, examining the characteristics of DLTs associated with these manifestations, and assessing the influence of digital fatigue on students' perceived performance. Meanwhile, qualitative methods, specifically a systematic review, address RQ4 by providing an in-depth exploration of strategies to manage or alleviate IO. This integration enabled the study to merge theory-based perspectives with empirical findings, ensuring alignment with the overall research objectives.

Table 3.3: Rationales for Mixed Methods Research (Bryman, 2006)

Rationale	**Description**
Triangulation	- Employs both quantitative and qualitative methods to allow for mutual validation of results. - Convergence of findings may also occur as an unintended outcome when the study's primary purpose was not explicitly triangulation.

Rationale	Description
Expansion	- When findings from the first phase need further explanation, qualitative insights help provide context. - Helps address unexpected results that require additional exploration.
Exploration	- Initial phase is used to develop tools, interventions, or identify variables for further study. - Useful for forming hypotheses that will be tested in subsequent research phases.
Completeness	- Combines methods to capture a fuller and more detailed picture of the subject under study.
Offset Weaknesses	- Minimises limitations inherent in each method, creating a stronger overall approach. - Requires each method to maintain rigorous standards on its own.
Different Research Questions	- Allows the study to address both quantitative and qualitative questions, as well as questions integrating both approaches.
Illustration	- Uses qualitative data to add context and depth to quantitative results. - Provides added detail or 'meat on the bones' to numerical findings.

3.5 Outline of Research Phases

This research progressed through four distinct phases, each tailored to meet its objectives. In the first phase, a literature review was conducted. This review encompassed an analysis of current trends in IO and an examination of how DLTs are integrated into educational environments. In the second phase, the research focuses on the development of the conceptual framework and the formulation of associated hypotheses. The third phase employed a quantitative approach to test this framework, utilising a survey methodology (administered to undergraduate students in UK higher education institutions). The survey, conducted via online questionnaires, enabled data collection from this sector. The final phase consisted of a systematic review to identify and analyse strategies for dealing with IO. These research phases exhibit distinct characteristics while also demonstrating interconnections, as depicted in Figure 3.1, which illustrates the research procedure components for this research. This chapter describes every technique and supports the research's stages.

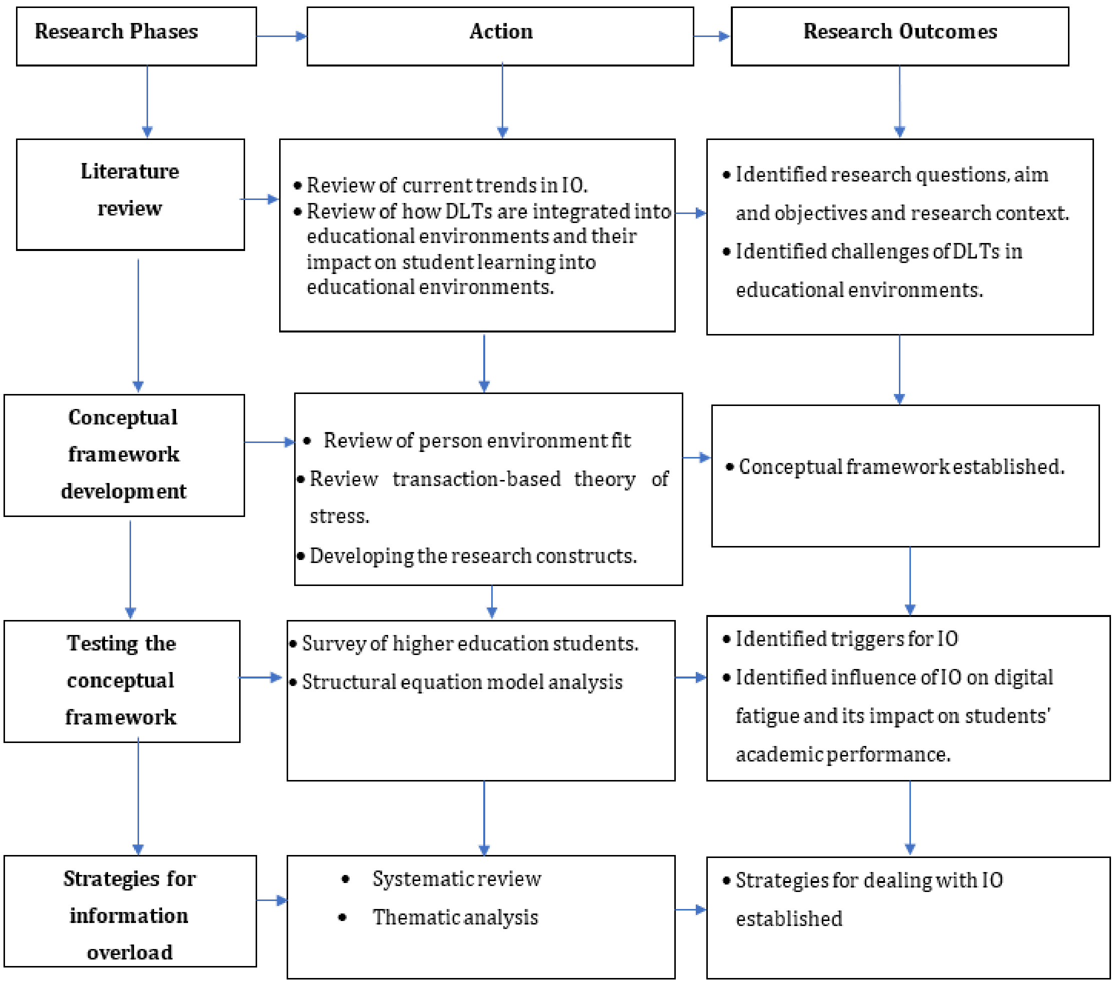


Figure 3.1: Diagram illustrating the sequential phases of the research methodology

3.6 Phase 1: Literature Review

This phase begins with an in-depth literature review of IO and an examination of how DLTs are integrated into educational environments, with a particular focus on the negative consequences of IO, such as digital fatigue and their impact on student learning. The preliminary literature review (not to be confused with the more specific systematic review undertaken in Phase 4, as described below) aims to identify the research questions, objectives, and overall research context, including the challenges associated with implementing DLTs in educational settings. The outcomes of this stage include a clear definition of the research questions, aims, objectives, and the contextual framework for the study. This research was conducted within the context of higher education, specifically focusing on the experiences of undergraduate students using DLTs in the post-COVID-19 era in the UK. While numerous studies were carried out to explore DLTs prior to the COVID-19 pandemic (Lee et al., 2016a; Zhang et al., 2016) and during it (Al Abdullateef et al., 2021; Alheneidi, 2019; Conrad et al., 2022; Fu et al., 2020; Zhang et al., 2022a), post-pandemic research is still tentative and emerging, and there is a need for more extensive research into all aspects of the development of DLTs in theory and practice given the galvanisation of such tools during the pandemic experience. Additionally, it identifies the challenges associated with the use of DLTs in educational environments, offering valuable insights into the complexities and limitations faced by students. This review lays the groundwork for the subsequent phases of the research. The initial review, conducted between 2021 and 2022, provided a foundational understanding of the prevailing scholarly discourse. This review was later updated and expanded during the stages of data collection, analysis, and thesis writing, spanning from 2023 to the final submission in 2025.

3.7 Phase 2: Developing the Conceptual Framework

This phase focused on developing a conceptual framework to address the following objective:

Objective 1: To develop a conceptual framework for IO within the context of DLTs through literature integration, serving as the foundational theoretical structure underpinning the investigation into RQ1, RQ2, and RQ3.

A conceptual framework is a structured representation of the key constructs, variables, and their interrelationships that underpin a study. It serves as a blueprint for the research, providing clarity on how theoretical concepts are linked to the research objectives and questions. According to Ager and Strang (2008), it synthesises theories and existing literature into an integrated structure, enabling researchers to identify and analyse complex phenomena.

This research develops a conceptual framework to investigate IO phenomenon within the context of DLTs. By synthesising theoretical perspectives from the *person-environment fit model* (P-E) and the *transactional-based theory of stress* (TBTOS), the framework examines the intricate interactions between individual cognitive capacities and environmental demands that contribute to the complexity of IO. The framework was developed to include four dimensions of IO (content overload, communication overload, system features overload, and social overload) based on recurring patterns in the reviewed literature. These dimensions were structured to be examined in the later stages of the study. The conceptual framework for this research was developed through the steps described below:

1. Reviewing existing literature: A literature review was conducted to examine relevant theories, frameworks, and empirical studies related to IO phenomena within the context of DLTs. Research studies relevant to this topic were retrieved from a variety of databases, including ProQuest: Library and Information Science Abstracts, SAGE, Elsevier, Emerald, Taylor & Francis, Scopus, and the Educational Resources Information Center (ERIC). Additionally, the University of Strathclyde's library search system (SUPrimo) was utilised to access the latest studies pertinent to this research. This process synthesised data from diverse fields, such as information science, psychology, and educational technology.

2. Theoretical synthesis and integration: Insights from established theories in this

field, particularly the P-E fit model and TBTOS, were integrated to provide a cohesive understanding of how the interaction between an individual's capacities (e.g., skills, knowledge, and time) and the demands of their environment (e.g., information volume or digital tool complexity) generates stressors (i.e., overload) and psychological strain (i.e., digital fatigue). This strain ultimately influences outcomes such as perceived academic performance, as detailed later in the conceptual framework in Chapter 4.

3. Identifying key dimensions of information overload: Recent research on IO unanimously acknowledges its inherent complexity. Various types of overload have been identified in the literature, all closely associated with IO, suggesting that it is best understood as a types construct, held together by patterns of overlapping and nonoverlapping features: content overload (volume), communication overload (multi-channels), system features overload (dynamic), and social overload (interaction). Stressors were categorised based on their underlying triggers (e.g., information volume, hyperconnectivity) and their specific relevance to the context of DLTs, as detailed later in the conceptual framework in Chapter 4.

4. Determining the moderating role of technology self-efficacy: Drawing on the P-E fit model Ayyagari et al. (2011); Cooper et al. (2013), which emphasises the role of dispositional variables in the relationship between stressors and strain, this research incorporates the moderating effect of technology self-efficacy. Dispositional traits influence how individuals cope with stressors. Those with greater technological self-efficacy are better able to adopt proactive coping strategies (e.g., seeking help, troubleshooting, or adapting to new technologies), which can buffer the negative effects of stressors. In contrast, individuals with low self-efficacy may struggle to cope effectively, resulting in greater strain and more pronounced emotional consequences, such as digital fatigue. In this research, technology self-efficacy serves as a buffer, reducing the negative impact of stressors (e.g., dimensions of IO) on outcomes like digital fatigue, thereby mitigating the adverse effects of IO.

5. Feedback and refinement: The initial framework was refined through discussions with academic supervisors and iterative reviews. Resultant feedback was incorporated to ensure that the framework was conceptually robust and aligned with the research's objectives, questions, and methodology.

6. Visualised operationalisation: The finalised framework was visually represented to illustrate the relationships between constructs (triggers, stressors, strain, and outcomes). This representation served as a guide for developing hypotheses.

3.7.1 The conceptual framework consists of four primary components:

1. **Triggers:** including the four key characteristics of DLTs 'information characteristics' (information volume, information irrelevance, and information equivocality), 'communication characteristics' (hyperconnectivity and interruption), 'engagement characteristics' (excessive interactions), and 'dynamic characteristics' (pace of change and complexity).

2. **Stressors:** encompassing the dimensions of information overload (content, communication, system features, and social overload); these external stimuli contribute to feelings of stress.

3. **Strain:** reflects the individual's response to these stressors, manifesting in symptoms such as digital fatigue.

4. **Outcomes:** captures the potential impact on perceived academic performance.

3.8 Phase 3: Testing the Conceptual Framework

This phase employed an online questionnaire to address the following objective:
Objective 2: To empirically test this conceptual framework model via a questionnaire to address RQ1 (identifying IO dimensions), RQ2 (determining associated DLT characteristics), and RQ3 (assessing the influence of digital fatigue on perceived academic performance).

Following the development of the conceptual framework, the subsequent phase focused on its empirical testing. This study employed an online questionnaire to collect data, evaluate the proposed model, and investigate students' usage of DLTs in their academic activities, with a focus on IO and its potential influence on their perceived academic performance. Data collection methods are essential considerations when conducting research, as the appropriate selection of these methods enables researchers to effectively meet the research's objectives. Creswell and Creswell (2023) emphasised the importance of distinguishing between two primary types of data collection: primary and secondary. Primary data refers to new information gathered directly by the researcher specifically for the research, typically obtained through experiments, interviews, observations, or questionnaires (Saunders et al., 2019; Schoonenboom and Johnson, 2017). In contrast, secondary data comprises previously collected information, initially gathered for other purposes (Creswell and Creswell, 2017). Qualitative methods can include focus groups and interviews, whereas quantitative methods generally involve the use of questionnaires, semi-structured interviews, and telephone surveys (Denscombe, 2021).

Surveys are a popular research method, particularly in fields like social science, management, and information science (Saunders et al., 2019). Typically linked to a deductive approach, surveys are efficient for collecting large-scale data (Creswell and Creswell, 2017).

According to Creswell and Creswell (2023), surveys primarily collect data from a sample of a studied population, which is then analysed statistically and generalised for the broader population being studied. This method allows researchers greater control over the study process and provides a cost-effective means of gathering large amounts of data from a representative sample of a studied population (Denscombe, 2021). The deductive approach is typically used in conjunction with surveys, where researchers begin with a theory, develop *a priori* hypotheses, and then collect and analyse data to test the hypotheses (Creswell and Creswell, 2017). The survey method offers several benefits, including its suitability for various examination techniques, question structure, population type, response rate, data collection timeline, and cost-effectiveness (Saunders et al., 2019).

Previous studies used a quantitative method to examine how various aspects of DLTs, such as information volume, information relevance, and frequency of interactions, can overlaod users and lead to strain. This strain often manifests as digital fatigue (Cao and Sun, 2018; Conrad et al., 2022; Fu et al., 2020; Islam et al., 2021; Lee et al., 2016a; Sheng et al., 2023; Zhang et al., 2022a), reducing students' engagement and impacting their ability to perform academically (Al Abdullateef et al., 2021; Alvarez-Risco et al., 2021; Shi et al., 2020; Yu et al., 2019). In pursuing these objectives, all of these studies adopted survey-based questionnaires to systematically gather data, ensuring a robust collection of quantitative insights to meet their research objectives.

3.8.1 Questionnaire Design

As mentioned above, survey design provides a structured methodology for gaining a quantitative understanding of trends, attitudes, and opinions within a population. It involves systematically collecting data from a sample to make inferences about broader characteristics or to test associations among variables (Creswell and Creswell, 2023). This research employs an online survey method, allowing for the efficient collection of data from a large sample and ensuring a rapid turnaround in data gathering. Moreover, a well-designed questionnaire is crucial for collecting accurate and reliable data. By ensuring the questionnaire is appropriate and engaging, researchers can maximise participant involvement and data quality (Sarstedt et al., 2019b; Teddlie and Tashakkori, 2012). A valid questionnaire facilitates accurate data collection, while a credible one ensures data consistency. Moreover, previous research has shown that a five-point Likert scale is an effective method for measuring opinions, as it is easy to understand and can increase response rates and quality while reducing respondent burden. (Saunders et al., 2019). The questionnaire design process involves a series of systematic steps aimed at ensuring the clarity, relevance, and effectiveness of the questionnaire. These steps, adapted from (Iacobucci and Churchill, 2010), include identifying the required information, crafting the content and structure of questions, determining their sequence, refining their wording, and conducting pilot testing to validate the design. Table 3.4 outlines the questionnaire development process.

Table 3.4: The Questionnaire Design Process (Adapted from Iacobucci and Churchill (2010)

Step	Description of the Questionnaire Design Process
1	Identify the information required for the research.
2	Define the content of the questions to align with research objectives.
3	Decide on the structure of the questions (e.g., open-ended or closed-ended).
4	Select precise and clear wording for each question.
5	Determine the sequence and flow of the questions.
6	Design the layout and visual appearance of the questionnaire.
7	Revise and refine the questionnaire based on feedback.
8	Conduct pilot testing to evaluate and finalize the questionnaire.

Using online questionnaires offers a cost-effective, time-efficient means of data collection (Schmitt et al., 2021). In this research, the survey was administered via Qualtrics and comprises nine sections (see Appendix A). Drawing on the literature, the researcher organised these sections into a coherent structure, as detailed below:

Section 1: Demographic Information

This initial section collected essential background information from participants, including their age, gender, academic major, and current academic year (4 items).

Section 2: Characteristics of Information

This section delves into the characteristics of information, focusing on three constructs: information volume, information irrelevance, and information equivocality (9 items).

Section 3: Characteristics of Communication

This section explores the characteristics of communication, focusing on two constructs: hyperconnectivity and interruption (6 items).

Section 4: Characteristics of Engagement

This section explores the characteristics of engagement, focusing on a single construct: excessive interaction (3 items).

Section 5: Dynamic Characteristics

This section examines the dynamic characteristics, focusing on two constructs: pace of change and complexity (6 items).

Section 6: Dimensions of Information Overload

This section examines the IO dimensions, focusing on four constructs: content overload, communication overload, social overload, and system features overload (12 items).

Section 7: Digital Fatigue

This section explores the construct of digital fatigue (3 items).

Section 8: Perceived Academic Performance

This section examines the construct of perceived academic performance (4 items).

Section 9: Technology Self-Efficacy

This section explores technology self-efficacy (3 items).

3.8.2 Survey Design Considerations

In designing the survey for this research, a deliberate approach was taken to incorporate both positively and negatively worded questions. This strategy offers several benefits (Chyung et al., 2018):

- Reducing acquiescence bias: this bias occurs when respondents tend to agree with statements regardless of their content. By including negatively and positively worded items, respondents are encouraged to think more carefully about each statement, reducing the likelihood of automatic agreement.

- Minimising extreme response bias: some respondents might consistently choose the most extreme options on a scale (e.g., always selecting "Never" or "Always"). Mixing positive and negative items can help balance these tendencies and provide more accuracy.

- Enhancing data quality: alternating item wording can make respondents more attentive and engaged, leading to more thoughtful and reliable responses

However, a potential limitation of using mixed wording, particularly with reverse-scored items, is the risk of researchers inadvertently overlooking the need to reverse scores during data entry. This oversight can lead to inaccurate data and potentially compromise the validity of the results. While data entry software can assist in recording user input, meticulous attention to detail is crucial to ensure that reverse-scored items are appropriately adjusted. Such errors may not always be readily apparent and can remain undetected throughout the analysis phase. To mitigate this risk, rigorous data checks were conducted throughout the entire analysis process.

3.8.3 Operationalisation of Constructs

Prior to developing a data collection tool, researchers must carefully define how theoretical concepts will be measured in practical terms (Creswell and Creswell, 2017). Operationalisation is the process of transforming abstract theoretical constructs into measurable, observable elements by specifying the specific actions, indicators, or processes that will be used to identify and quantify those concepts in the research context (Easterby-Smith et al., 2021). Each theoretical construct in the research requires a clear, systematic approach to measurement, involving the precise definition of scale items and the selection of an appropriate scale type for effective data collection (Creswell and Creswell, 2023). The development of each construct in this research was guided and informed by existing research and literature within the relevant field, drawing upon previous scholarly works to establish a robust conceptual framework. The research operationalised the information characteristics construct through a carefully curated set of measurement items involving three questions to measure information volume, which was adapted from Chen et al. (2012) research and changed to suit the context of DLTs. Similarly, the assessment of information irrelevance comprised three items taken from a recent study Guo et al. (2020), and information equivocality was adapted from Lee et al. (2016a). The measurements of communication characteristics constructs included the use of three questions to measure hyperconnectivity based on Ayyagari et al. (2011); Fredette et al. (2012). Interruptions were established on the prior study of McFarlane and Latorella (2002). The measurements of communication dynamic characteristics contained the use of three items pace of change and complexity were adopted from Ayyagari et al. (2011).

Digital fatigue was measured through three items from prior work by Alvarez-Risco et al. (2021). Measurements of engagement characteristics encompassed three items, excessive interaction was modified from Laumer et al. (2013). Measurements of content overload, system-features overload, and communication overload each drew on three items adapted from Karr-Wisniewski and Lu (2010) and Lee et al. (2016a), while social-overload three items were modified from Maier et al. (2015b). Technology self-efficacy was measured through four items based on the study of Delpechitre et al. (2019). Perceived academic performance was established through three items from Alvarez-Risco et al. (2021).

3.8.4 Limitations and Mitigation: Disentangling Academic from Non-Academic Use

A recognised challenge in treating SNS as DLTs is the co-presence of non-learning content ("ambient" streams) that may inflate perceived overload independently of academic tasks. For clarity, this study defines academic use of SNS as the extent to which students engage with these platforms for learning-related purposes (e.g., accessing course materials, coordinating group work, and sharing academic resources .To mitigate this risk and align measurement with the study's construct definitions, the following steps were taken:

- **Operational scope communicated to participants:** The participant information sheet, consent wording, and item stems explicitly instructed respondents to consider only SNS activities undertaken for academic or learning purposes (e.g., joining course groups, sharing readings, coordinating group work), and to exclude purely recreational/social browsing (see Appendix C).
- **Context-anchored item wording:** Measurement items referenced learning-relevant behaviours (e.g., "course announcements", "assignment coordination", "discussion of course materials"), reducing the likelihood that responses reflected non-academic usage.
- **Constructs that model the 'ambient' effect:** Rather than treating off-task

exposure as error, constructs such as *information irrelevance*, *excessive interactions*, and *social overload* were included as theory-driven pathways through which SNS usage can translate into overload and fatigue in authentic conditions (Lee et al., 2016a; Maier et al., 2012).

- **Pretesting for interpretive clarity:** Academic and undergraduate pilot participants confirmed that instructions and examples successfully foregrounded learning-purposed SNS use and reduced ambiguity (Section 3.8.7).

3.8.5 Rationale for Using the Likert Scale Frequency

This research employed a five-point frequency-based Likert scale to capture students' perceptions of IO (with the response options 'Never', 'Rarely', 'Sometimes', 'Often', and 'Always'). This approach enables respondents to indicate how frequently they feel overwhelmed by DLTs, such as replying to emails or instant messages, participating in online forums, or managing numerous notifications. (Sarstedt et al., 2019b; Sullivan and Artino Jr, 2013). The advantages of employing a frequency-based Likert scale are summarised in Table 3.5.

Table 3.5: Advantages of using a frequency-based Likert scale

Benefit	**Description**
Quantitative data	Provides numerical data that is easy to analyse and interpret.
Versatility	Can be used to measure a wide range of opinions and attitudes.
Efficiency	Reduces respondent burden by providing structured response options.
Higher response rates	Encourages participation by offering a quick and easy survey format.
Reliable and valid data	When well-designed, Likert scales can yield reliable and valid results.

3.8.6 Sampling Frame

Selecting appropriate sampling techniques and determining the right sample size are inherently complex processes that demand careful consideration. An unsuitable sampling strategy can lead to significant inefficiencies in the research process and introduce bias. Determining the appropriate sampling technique is a crucial aspect of the research process to ensure the collection of relevant data. Sampling involves selecting individuals who will participate in the study, representing the target population and contributing to the overall validity of the findings. A sampling frame is a comprehensive list or database of the entire population eligible for inclusion in a survey, serving as the basis for selecting a sample. Once the population of interest is defined, the researcher identifies and establishes the suitable sampling frame (Saunders et al., 2019). The sampling frame encompasses the resources and elements that represent the identified components of a population (Creswell and Creswell, 2023). The sampling process should be carefully designed with consideration of the following factors Creswell and Creswell (2023); Saunders et al. (2019):

- Target Population: the sampling unit specifies the group of people who will be surveyed.
- Sample Size: the sample size determines the number of participants needed to represent the target population.
- Sampling Method: the sampling technique outlines the process for selecting participants from the target population.

The population for this research consists of undergraduate students in UK higher education who use DLTs as part of their academic activities. Undergraduate students were selected as the target population for several reasons. They represent a large and diverse segment of the higher education community and are highly engaged with DLTs in their day-to-day learning. The Student Digital Experience Insights report shows that 85% of students rate their digital learning environment as above average, while 78%

confirm they have access to learning platforms. Additionally, undergraduates made up the majority of respondents (60%), underscoring their prominent role in UK higher education and their engagement with digital tools (Jisc, 2023). Previous studies have indicated that undergraduate students are more likely to rely on a variety of digital learning tools—including learning management systems, online forums, and communication platforms—for coursework, collaboration, and assessment. For instance, Al-Hail (2023) highlighted the significance of digital and social media tools in enhancing learning experiences during and after the COVID-19 pandemic (Al-Hail, 2023). Similarly, Rafiq and Khan (2024) emphasised the role of these tools in improving student engagement and academic performance in higher education (Rafiq and Khan, 2024). Additionally, existing literature suggests that undergraduate students are particularly vulnerable to IO (Ager and Strang, 2008; Alheneidi, 2019; Conrad et al., 2022; Xie and Tsai, 2021). Focusing on this group thus allows for a deeper understanding of how DLT-driven IO affects learners' learning experiences and academic performance, thereby informing more targeted interventions and support strategies within universities.

Sampling methods can be categorised into two main types: probability (e.g., simple random, stratified, systematic, and cluster sampling) and non-probability (e.g., convenience, quota, self-selection, snowball, and purposive sampling). Probability sampling ensures that each member of the population has a known chance of being selected for the sample (Easterby-Smith et al., 2021; Saunders et al., 2019), and offers the ability to generalise findings to the broader population. In contrast, non-probability sampling does not guarantee that every member of the population has an equal chance of being selected. While non-probability sampling methods are practical and cost-effective, they cannot provide precise estimates of population characteristics (Creswell and Creswell, 2023).

This research employed a non-probability sampling method. A convenience sampling method was employed in this research, whereby students were selected based on their availability and accessibility. Convenience sampling is a time-efficient and cost-effective method. Researchers can easily select participants without extensive effort or cost. As the sample is readily accessible, less time is invested in participant selection. Moreover, it eliminates the need to create a comprehensive list of the entire population. This technique can also provide valuable qualitative data. However, convenience sampling has several drawbacks, including potential bias and limited generalisability for the broader population. Self-selection bias can arise, as participants themselves choose whether to participate (Golzar et al., 2022).

Etikan et al. (2016) noted that convenience sampling is a non-probability sampling method where participants are selected based on their immediate availability and willingness to participate. Consequently, participants in this study were chosen using a convenience sampling method, selecting those who were readily available.

Sample Size

This phase is of a quantitative nature. The survey was created using the information found in the relevant literature. Its items were assessed on a five-point Likert-type scale, with responses ranging from 1 (Never) to 5 (Always) (Creswell and Creswell, 2017). Prior studies have demonstrated that respondents easily understand a five-point scale to articulate their opinions, and this boosts response rate and quality while decreasing respondents' irritation level (thus making it more likely that they will complete the instrument, and give realistic data). The data were collected from students on an individual basis. To qualify, participants had to meet the sample inclusion and exclusion criteria, which are discussed in detail in a later section 3.8.8.

Larger sample sizes are generally preferred for component analysis (Sekaran, 2017). However, (Leguina, 2015) suggests that a sample size of over 100 is ideal for factor analysis and recommends a ratio of at least five participants per questionnaire variable. Based on the number of variables in this research, a sample size exceeding 170 would be appropriate. Moreover, partial least squares structural equation modelling (PLS-SEM) is well-suited for handling smaller sample sizes and complex models (Hair et al., 2021), sample size requirements are not universally applicable across all models. Reinartz et al. (2009) demonstrated through simulation that PLS-SEM is an effective method for handling limited sample sizes. They suggested that with at least 100 observations, it is possible to achieve acceptable levels of statistical power, provided the measurement model is of good quality. Insufficient sample sizes can undermine construct validity (Creswell and Creswell, 2017; Saunders et al., 2019), potentially leading to poorly fitting models. Therefore, a minimum sample size of 100 is recommended for PLS-SEM analysis, which this research has adhered to by employing a sample of 200 participants.

3.8.7 Questionnaire Pilot Research

To guarantee that the research objectives are met, it is essential to ensure that participants fully comprehend the questions and can provide answers in the desired format (Creswell and Creswell, 2017; Easterby-Smith et al., 2021). Consequently, conducting a pilot test at the beginning of data collection is a standard practice to identify and rectify any ambiguities or misunderstandings (Easterby-Smith et al., 2021; Saunders et al., 2019). The pilot study in this research aimed to validate the proposed model and identify potential issues within the questionnaire, focusing on clarity, language, layout, and length. Additionally, the researcher sought to eliminate ambiguity and misunderstanding, optimising the survey for participant engagement. The survey structure was deliberately designed to be concise and user-friendly, with the goal of maximising participation rates. To ensure its effectiveness, the survey underwent a series of pilot studies involving two distinct groups:

- Academic review: In November 2023, a pilot test was conducted with 9 PhD students from the University of Strathclyde, who provided feedback on question clarity, potential misunderstanding, and the overall structure of the survey.

- Undergraduate students: In November 2023, a pilot test was conducted with a group of 10 undergraduate students above age 18 drawn from other UK higher-education institutions via the Prolific platform. This phase ensured the proper functioning of all technical aspects, provided insights into participant responses, and verified the accuracy of the estimated completion time. Prolific's built-in timing data showed that the median time to complete the final nine-section questionnaire was 7 minutes.

Building on the pilot studies, the researcher refined the survey's structure, language, and visual design for optimal clarity and user-friendliness. By eliminating ambiguity, the survey was made more accessible and reliable, ensuring accurate and valuable data collection.
The researcher then presented the final questionnaire design to his supervisors, who approved its activation and distribution to undergraduate students in the UK. The finalised version of the questionnaire can be found in Appendix A.

3.8.8 Sample Inclusion and Exclusion Criteria

Research participants (undergraduate students) were recruited via the Prolific platform, which is recognised for its reliability in research participant recruitment, ensuring voluntary participation and fair compensation, fostering ethical and high-quality data collection (Eyal et al., 2021). Eligibility for the sample was determined using Prolific's prescreening system, which selects participants based on specific criteria to guarantee the suitability of the sample for the research. The eligibility requirements for this research included the following:

- Age: 18 years or older.
- Country of residence: United Kingdom.
- Student status: enrolled as undergraduate students.
- Year of study: participants must be in their 1st, 2nd, 3rd, or 4th year of undergraduate studies.

The pilot studies were conducted with a combined total of 19 students (9 PhD students and 10 undergraduate students), who were subsequently excluded from the main data analysis. Consequently, the final usable sample size for the quantitative analysis comprised 200 participants. A total of 200 participants were successfully recruited via Prolific, and their responses were essential for measuring their IO when using DLTs in their study-related activities.

3.8.9 Ethical Consideration

To ensure research integrity and accuracy, Saunders et al. (2019) emphasised the importance of adhering to ethical guidelines throughout the research process. Participants were informed of their rights to privacy, anonymity, and confidentiality (Creswell and Creswell, 2017). This study strictly followed the ethical frameworks established by the Department of Computer and Information Science at the University of Strathclyde to ensure compliance and maintain research integrity. Ethical approval was granted by the Ethics Committee of the same department, registered under Application [ID: 2425] (see Appendix B and Appendix C).

3.8.10 Questionnaire Data Analysis Strategy

Selecting the most appropriate statistical technique represents a critical initial phase in research analysis, requiring meticulous evaluation of multiple research components. Researchers must carefully assess research objectives, guiding questions, aims, data characteristics, and the specific features of statistical instruments to ensure methodological rigour (Creswell and Creswell, 2017; Easterby-Smith et al., 2021).

Prior to implementing any analytical approach, a comprehensive examination of these factors is essential to optimise research procedures, allocate resources effectively, and generate accurate, meaningful conclusions (Saunders et al., 2019). In this research, a preliminary review of questionnaires was conducted to validate their appropriateness. The data collection process involved administering an online questionnaire to undergraduate students in United Kingdom higher education institutions. The research successfully recruited 200 participants through the online survey Prolific platform. Following a detailed review, all questionnaires were found to be fully completed, with no instances of missing data. Consequently, the researchers were able to include the entire sample of 200 responses in their subsequent analysis, ensuring a comprehensive and robust dataset for investigation. Drawing on insights from undergraduate students, this dataset enhances the research's thoroughness and significance. The statistical analyses employed in this research are detailed below.

Descriptive Statistics

Descriptive statistics transform raw data into an interpretable format, thereby enhancing its comprehensibility and analytical value. This statistical approach encompasses various techniques such as graphical representations, frequency distributions, and dispersion analysis (Creswell and Creswell, 2017). In this research, descriptive statistical methods were used by systematically organising, summarising, and characterising the collected data, offering a clear representation of the sample's key attributes and underlying patterns. The descriptive analysis was conducted using the built-in statistical tools available within the Qualtrics platform.

Partial Least Squares Structural Equation Modeling

Partial Least Squares Structural Equation Modeling (PLS-SEM) is a robust statistical technique for analysing complex relationships between observed and latent variables (Hair et al., 2021). In this study, PLS-SEM was employed as part of a deductive research approach to test hypotheses derived from the conceptual framework. By using this method, the study rigorously examines both the measurement and structural models, enabling the analysis of direct and indirect effects, mediation processes, and the relationships between theoretical constructs.

PLS-SEM is a predictive causal approach to SEM, emphasising prediction in statistical model estimation. At the same time, the structure of the models is designed to provide causal explanations (Sarstedt et al., 2019a). Although it is frequently applied in exploratory research, in this stage of the thesis, it is used deductively to evaluate theoretically grounded hypotheses. By combining causal–explanatory rigour with predictive capability, PLS-SEM allows the study to validate the conceptual framework while also generating meaningful theoretical and practical insights (Hair et al., 2021).

The key advantages of PLS-SEM are summarised in Table 3.6 (Hair et al., 2021):

Table 3.6: Key advantages of PLS.SEM. Adapted from (Hair et al., 2021)

Aspect	Details
Flexibility with Small Sample Sizes	- Works effectively with smaller datasets where covariance-based SEM might struggle - Robust when sample sizes are limited
Distribution Assumptions	- Does not require strict normality of data - Tolerant of non-normally distributed variables - Suitable for complex, real-world datasets with skewed or non-linear distributions
Complex Model Handling	- Capable of handling complex models with multiple latent variables - Can simultaneously analyze measurement and structural models - Manages models with many constructs and indicators
Predictive Orientation	- Emphasizes prediction and explanation of variance - Particularly useful for exploratory and theory-building research - Focuses on maximizing explained variance in dependent constructs
Versatility Across Disciplines	- Widely applicable in management, marketing, social sciences, technology acceptance studies - Handles both reflective and formative measurement models
Computational Efficiency	- Computationally less demanding compared to covariance-based SEM - Faster estimation of model parameters - Suitable for complex models with many variables

Aspect	Details
Handling Multicollinearity	- More robust when dealing with highly correlated predictor variables - Reduces issues of multicollinearity in complex models

PLS-SEM presents some limitations, notably its difficulty with non-recursive models and the lack of broadly recognised global goodness-of-fit statistics (Hair et al., 2021). These factors make it less suitable for theory testing compared to Covariance-Based SEM (CB-SEM), which prioritises the assessment of model fit. Nevertheless, PLS-SEM's focus on causal prediction, while considered less stringent, provides robust predictive capabilities and practical utility, rendering it particularly valuable for research aimed at producing actionable recommendations (Hair et al., 2021).

3.8.11 Suitability of PLS-SEM for Likert Scale Data

PLS-SEM is widely applied in studies using Likert-type survey data to model latent constructs that cannot be directly observed (Al Abdullateef et al., 2021; Alvarez-Risco et al., 2021; Hair et al., 2021). In this study, a frequency-based Likert scale (Never, Rarely, Sometimes, Often, Always) was employed to capture participants' behavioural tendencies. Although these categories are inherently ordinal, they were systematically transformed into numerical values (e.g., 1 = Never through 5 = Always) prior to analysis. This transformation assumes that the categories are ordered along a continuum of frequency, with each step representing a meaningful progression in behaviour. By assigning numerical scores, the responses can be treated as interval data, which is necessary for techniques such as PLS-SEM.

This treatment of Likert data is well established in methodological literature. While the scale does not guarantee truly equal distances between categories, the assignment of consecutive integers provides a practical approximation. Furthermore, PLS-SEM is a variance-based method that is robust to deviations from normality and can accommodate ordinal data treated as interval-level without introducing substantial bias (Hair et al., 2021; Rigdon, 2016). In addition, the use of multiple Likert items aggregated into constructs reduces random measurement error, thereby increasing the validity of treating the numerical scores as continuous indicators of latent variables.

3.8.12 Drawbacks of Likert Scale

Despite the advantages outlined in Section , frequency-based Likert scale data also present several limitations.

- Ordinal structure: The exact “distance” between adjacent categories (e.g., Rarely vs. Sometimes) may not be equal, which challenges the assumption of interval-level measurement (Jamieson, 2004).
- Response biases: Respondents may favor midpoints (Sometimes) or avoid extreme categories (Never or Always), leading to central tendency bias.
- Subjective interpretation: Terms like Often or Sometimes may not be interpreted uniformly across respondents.
- Limited variance: With only five categories, the scale restricts response variation, which may reduce the sensitivity of statistical models.

In conclusion, while frequency-based Likert data are not interval by design, their transformation into numerical values is widely practiced and considered acceptable for PLS-SEM analyses. The method’s tolerance for non-normal and ordinal data strengthens the justification for its use in this study.

3.8.13 Testing Theoretical Association

In developing path models, two key components must be assessed: the measurement theory and the structural theory. The measurement theory focuses on identifying and evaluating the indicators used to represent theoretical constructs, ensuring they accurately and consistently measure the intended concepts. In contrast, the structural theory defines and tests the hypothesised relationships between those constructs (Hair et al., 2021).

The evaluation process begins with the measurement model, where the validity and reliability of the indicators are thoroughly examined. Only after confirming that the measurement model meets these standards can researchers proceed to assess the structural model. This sequence is crucial, as without valid and reliable measures, any conclusions drawn from the structural relationships would be fundamentally flawed.

3.8.14 Measurement Theory

Before assessing structural relationships in a path model, it is crucial to ensure that constructs are measured accurately and consistently. Grounded in measurement theory, this involves evaluating the reliability and validity of the measurement model. In PLS-SEM, this assessment follows several key steps (Hair et al., 2021):

- **Indicator Reliability**

The first step in assessing a measurement model involves evaluating how much of each indicator's variance is explained by its construct, which indicates the reliability of the indicator. Indicator reliability reflects the commonality of an indicator. Loadings above 0.708 are recommended, as they indicate that the construct explains more than 50 percent of the indicator's variance, ensuring acceptable reliability. However, researchers often encounter weaker indicator loadings (below 0.708) in social science studies (Hair et al., 2021). In such cases, items with loadings between (0.40–0.70) should only be removed if doing so raises internal consistency or convergent validity above their threshold values. Indicators with loadings below 0.40, however, contribute little to the model and should always be eliminated (Hair and Alamer, 2022). For the present study, the following procedures were applied to evaluate indicator reliability:

- Ran the PLS algorithm to compute outer loadings.
- Inspected all indicators and noted those with loadings below 0.708.
- Removed indicators with loadings below 0.40, as these contributed little to the model. items with very low loadings (below 0.40). For example, the items for IE2,

IN2, and SO1, were removed from the analysis because their retention negatively impacted the model's internal consistency and convergent validity

- Retained indicators with loadings between 0.40–0.70 only if removing them improved internal consistency or convergent validity.

As a result, most retained indicators showed strong loadings (> 0.708), while weaker items were removed, ensuring indicator reliability in the model.

- **Internal consistency reliability**

This step evaluates how well indicators of the same construct correlate that is, their internal consistency reliability. Traditionally, Cronbach's alpha is used, to estimate reliability from the intercorrelations among observed indicator variables. However, because alpha can underestimate true reliability, it is often preferable to use composite reliability, which accounts for each indicator's outer loading. Composite reliability (rhoc) can, in turn, overestimate reliability. To strike a balance, the reliability coefficient (rhoA) (Dijkstra and Henseler, 2015) was introduced: it typically falls between Cronbach's alpha and composite reliability, offering a more precise compromise between conservative and liberal estimates (Hair et al., 2021). Following best practices (Dijkstra and Henseler, 2015; Hair et al., 2021):

- Cronbach's alpha, composite reliability (rhoC), and rhoA were computed for all constructs.

- Values were compared to recommended thresholds: alpha ≥ 0.70, rhoC ≥ 0.70.

In this research, Cronbach's alpha ranged from 0.709 to 0.873, composite reliabilities exceeded 0.70, and rhoA fell within an acceptable range, indicating strong internal consistency. For instance, Digital Fatigue had a Cronbach's alpha of 0.776 and a composite reliability (rhoC) of 0.871, indicating strong internal consistency

- **Convergent Validity**

The third step involves assessing the convergent validity of each construct, which is the degree to which a construct converges to explain the variance of its indicators. The metric used for evaluating convergent validity is the average variance extracted (AVE) for all indicators on each construct. AVE is defined as the grand mean value of the squared loadings of the indicators associated with the construct (i.e., the sum of the squared loadings divided by the number of indicators). Therefore, AVE is equivalent to the commonality of a construct. The minimum acceptable AVE is 0.50—an AVE of 0.50 or higher indicates that the construct explains 50 percent or more of the variance of its indicators (Hair et al., 2021). For the present research, the following procedures were applied to evaluate convergent validity:

- Calculated AVE for each construct.
- Checked that AVE ≥ 0.50.

All constructs in this study exceeded this threshold. For example, system features overload AVE = 0.792, and perceived academic performance AVE = 0.647.

- **Discriminant Validity**

The final step is to assess discriminant validity, which measures how distinct a construct is from other constructs in the structural model. Fornell and Larcker (1981) proposed a traditional metric for this purpose. They suggested comparing each construct's AVE (squared variance within) to the squared inter-construct correlation (a measure of shared variance between constructs) of that construct and all other reflectively measured constructs in the model. The shared variance between all model constructs should not exceed their AVEs (Hair et al., 2021).

Henseler et al. (2015) proposed the Heterotrait-Monotrait ratio (HTMT) as a more robust measure for evaluating discriminant validity. This method offers improved specificity and sensitivity compared to conventional techniques such as examining cross-loadings and the Fornell-Larcker criterion. According to their work, an HTMT value below 0.85 generally indicates that discriminant validity has been established. However, it is crucial to recognise that HTMT is not designed to identify collinearity issues among latent variables. In this research, this was tested using the Fornell-Larcker criterion, which requires that the square root of each construct's AVE is greater than its correlation with any other construct. All constructs satisfied this criterion. For example, the square root of the AVE for content overload (0.81) was greater than its correlation with all other constructs, including its highest correlation with communication Overload (0.72).

3.8.15 Structural theory

The assessment of the structural theory in PLS-SEM involves several key steps (Hair et al., 2021):

- **Evaluation of Collinearity:**

The process begins by examining potential collinearity among the predictor constructs within the structural model regressions. This is typically done by analysing the Variance Inflation Factor (VIF) values. Acceptable VIF values indicate that multicollinearity is not an issue and that the model estimates are reliable. Following Hair et al. (Hair et al., 2021), VIF values were computed based on construct scores derived from the measurement model. All predictor constructs exhibited VIF values ranging from 1.04 to 2.60, which fall well below commonly recommended thresholds, indicating that multicollinearity was unlikely to compromise the structural estimates."

- **Assessment of Path Coefficients:**

Once collinearity among predictor constructs was ruled out, the evaluation of path coefficients proceeded according to the following logical steps:

- Generation of Bootstrap Statistics: To assess the stability and reliability of the estimated path coefficients, a bootstrapping procedure with 10,000 subsamples was performed. This procedure generated t-values and 95% confidence intervals for each path.

- Estimation of Path Coefficients: Path coefficients (β), representing the hypothesised relationships between constructs, were estimated from the structural model. These coefficients reflect both the direction (positive or negative) and the magnitude of each effect.

- Assessment of Statistical Significance: A path was considered statistically significant if its 95% confidence interval did not include zero (corresponding to two-tailed critical values of $|t| \geq 1.96$, $p < 0.05$). This criterion ensures that the observed effect is unlikely to have occurred by chance.

- Interpretation of Results: The procedure was applied to evaluate all hypothesised relationships. Examples from the current study include:

- **Supported hypothesis example**: The path from information volume to content overload showed a significant positive effect ($\beta = 0.382$, $t = 6.121$). The 95% confidence interval [0.258, 0.501] did not cross zero, supporting Hypothesis H1a.

- **Rejected hypothesis example**: In contrast, the path from communication overload to digital fatigue was statistically insignificant ($\beta = 0.004$, $t = 0.041$). Its 95% confidence interval [-0.165, 0.172] included zero, leading to the rejection of the corresponding hypothesis.

- **Explanatory Power of the Model:**

Finally, the model's explanatory power is assessed using the coefficient of determination (R^2). This value indicates how well the independent constructs explain the variance in the dependent construct(s). The analysis in this research proceeded as follows: R^2 are computed for endogenous constructs to assess how well the predictors explain variance. For example, the R^2 value for digital fatigue was 0.581, meaning the four overload dimensions collectively accounted for 58.1 % of its variance. The model also explained 21.9 % of the variance in Perceived academic performance.

3.8.16 Data Validation

To ensure the accuracy and reliability of the data, a multi-step validation process was implemented. First, the questionnaire underwent two pilot studies—one with nine PhD students for academic review and another with ten undergraduate students via the Prolific platform—to assess clarity, language, layout, and technical functionality. Based on feedback, the instrument was refined and approved by academic supervisors prior to deployment. During data collection, Prolific's system enforced eligibility criteria and completeness checks, ensuring that only fully completed responses were submitted. After collection, all responses were reviewed for completeness, and reverse-coded items were verified to prevent scoring errors. Finally, statistical validation was conducted using PLS-SEM, including assessments of indicator reliability, internal consistency (Cronbach's alpha, composite reliability), convergent validity (average variance extracted), and discriminant validity (Fornell–Larcker criterion). These steps collectively ensured that the dataset was accurate, internally consistent, and suitable for hypothesis testing.

3.9 Phase 4: Strategies for Dealing with Information Overload

This phase employed a systematic review to address the following objective:
Objective 3: To conduct a systematic review of existing literature to determine IO management strategies (thereby answering RQ4).
Following the testing of the conceptual framework, the subsequent phase focused on a systematic review using a thematic analysis of 38 articles to provide insights into existing measures for the prevention and intervention of IO. The systematic review is a method for identifying, assessing, and interpreting all existing research related to a specific research question, topic, or phenomenon of concern with the eligibility criteria for studies being defined beforehand (Chandler et al., 2019; Kitchenham, 2004). The systematic review was created to ensure that decisions, particularly in healthcare, are based on the most current and comprehensive research evidence. As the volume of research continues to

grow, it becomes increasingly difficult for individuals to sift through this vast body of information (even within specialist academic fields). Systematic reviews provide a structured approach to summarising and evaluating this research, aiming to minimise bias and inform evidence-based decision-making. A systematic review seeks to gather all relevant empirical evidence that meets pre-defined eligibility criteria to address a specific research question (Chandler et al., 2019).

3.9.1 Benefits of Conducting Systematic Reviews

There are several compelling motivations for conducting a systematic review, each serving a distinct purpose in advancing knowledge and improving research practices. The primary reasons for undertaking such a review typically include the following (Chandler et al., 2019; Kitchenham, 2004)

- **To summarise existing evidence:** provides a comprehensive summary of the available evidence on a particular topic, helping to draw conclusions based on a wide range of studies. For example, it consolidates the benefits and limitations of a specific methodology or treatment.

- **To identify gaps in research:** highlights areas where research is lacking, suggesting directions for future investigation.

- **To Inform New Research:** offers a solid foundation or context to guide the design and focus of new research, ensuring that it addresses existing gaps and builds on previous findings.

- **To provide a reliable source of evidence:** offers a higher level of reliability and objectivity in synthesising evidence, making it a valuable resource for decision-making.

- **To assess interventions or practices:** evaluates the overall treatments, interventions, or practices, providing evidence for their implementation in real-world settings.

3.9.2 Rationale for Using Systematic Review in This Study

The decision to conduct a systematic review rather than a single-study (interviews) to address the research question, *'What strategies are used to manage or alleviate IO?'*, is grounded in several key justifications. A systematic review provides a structured and rigorous method to synthesise the state of knowledge in the area from diverse studies, ensuring a broader and more objective understanding of the strategies employed across different contexts and populations. This method is particularly well-suited for the research question, as it leverages a vast array of pre-existing data and peer-reviewed studies, saving time and resources compared to conducting primary research through interviews. While interviews offer in-depth insights from specific individuals, they are limited by sample size and scope, potentially introducing subjectivity and bias. In contrast, a systematic review enables clear and transparent documentation of the rationale for conducting the review (e.g., the methods used to locate and choose articles), thereby grounding its findings in rigorous methodology. Therefore, systematic reviews produce varied knowledge and insights, specifically beneficial for a broad audience of stakeholders, including educators, researchers, and policymakers (J et al., 2021).

3.10 Chapter Summary

This chapter provided the mixed-methods research methodology used to address the study's objectives. It outlines the rationale for integrating quantitative and qualitative methods, describing the literature review, conceptual framework, survey design, and systematic review. Additionally, it covers ethical considerations and data analysis strategies, statistical techniques for quantitative data.

Chapter 4

Conceptual Theoretical Framework

4.1 Introduction

This chapter establishes the conceptual and theoretical foundation for understanding IO in the context of DLTs. IO is a pervasive challenge across multiple disciplines, including psychology, information science, and education, where it is increasingly recognised as a multidimensional phenomenon with significant implications for cognitive, emotional, and behavioural outcomes. Despite the breadth of research on IO, many studies have approached it from singular perspectives, often overlooking its complexity and interconnected dimensions. The aim of this chapter is to provide a framework for examining IO by integrating relevant theories and identifying its core dimensions—content, communication, social overload, and system features. These dimensions serve as specific manifestations under the broader umbrella of IO and collectively capture the multifaceted nature of the phenomenon.

The chapter begins by exploring existing approaches to studying IO and identifying gaps in conceptualising it as a dynamic and multidimensional process. It then introduces the theoretical foundations underpinning this research, including the Person-Environment Fit Model and the Transactional-Based Theory of Stress. These theories offer complementary insights into how individual capacities and environmental demands interact to create experiences of overload, strain, and subsequent outcomes such as digital fatigue and impaired academic performance.

Finally, the chapter presents a detailed examination of the four key dimensions of IO—content, communication, social overload, and system features—and their interrelations. This integrated approach provides an understanding of how these dimensions manifest in digital learning environments, offering a solid foundation for hypothesis development and empirical analysis in the subsequent chapters.

4.2 Approaches to Studying IO

IO has been widely studied across various fields, including medicine, business, social sciences, and IS research, resulting in the use of numerous interchangeable terms (Alheneidi et al., 2021; Batista and Marques, 2018; Bawden and Robinson, 2020; Belabbes et al., 2023; Eppler and Mengis, 2008; Marques and Batista, 2017). However, most researchers do not conceptualise IO as a complex phenomenon encompassing multiple dimensions, as elaborated upon in this chapter.

The concept of IO has attracted interest across various disciplines, particularly in psychology, where research on stress has received significant attention. IO serves as a bridging concept, connecting the excess of information (an external reality) with the psychological responses of feeling stress (Alheneidi, 2019; Bawden and Robinson, 2020; Eppler and Mengis, 2008; Hartog, 2017; Mulder et al., 2006; Ragu-Nathan et al., 2008). Psychology research focuses on understanding the relationship between individual factors, such as traits, personality, and stress-related variables. In this research, insights from the stream of research are gleaned to understand IO with a well-rounded perspective.

A review of previous studies has found that overload is interpreted from a stress perspective as transactional stress (viewing overload as a dynamic process) (Al Abdullateef et al., 2021; Fakhfakh and Bouaziz, 2022; Shi et al., 2020) such as a stressor as an independent variable (Whelan et al., 2020; Xiao and Mou, 2019; Yu et al., 2019) or as a dependent variable (Ayyagari et al., 2011; Lee et al., 2016a; Maier et al., 2015a) which may lead to negative outcomes for individuals for example discontinuous usage (Fakhfakh and Bouaziz, 2022; Park and Koh, 2018) intention.

There is a growing consensus that overload arises from the interaction between the person and their environment (Cooper et al., 2001, 2013). From a transactional perspective, no single component—such as the stressor or the resulting strain—can fully explain overload. Instead, it must be understood as an outcome of an interconnected and complex process.

4.3 Theoretical Framework For Studying Information Overload

Before the theoretical framework is introduced, two perspectives that offer insights into the phenomenon of IO are examined.

The first viewpoint can be called a media-centric perspective. Media richness theory provides a theoretical framework for studying IO (Arnold et al., 2023; Daft and Lengel, 1986). However, this theory primarily focuses on the objective characteristics of media, such as feedback speed and the number of communication cues, while overlooking the subjective and dynamic nature of individual experiences. Individual factors, such as abilities, skills, and personal learning preferences, significantly influence how a medium is perceived and utilised. By ignoring these aspects, the media richness theory's relevance is limited, particularly in contexts like DLTs, where user adaptability and coping mechanisms are essential. Additionally, media richness theory does not address how individuals appraise stressors.

The other viewpoint could be called the cognitive perspective, which is essential for understanding IO. This perspective emphasises how individuals interpret and respond to information, which ultimately shapes the negative effects they experience as a result of overload or other factors (Belabbes et al., 2023; Sweller, 1988). Researchers in this field advocate for the use of subjective measures, such as individual perceptions of cognitive and social demands (e.g., those arising from DLTs), to better capture how users experience and respond to IO (Ayyagari et al., 2011; Chen et al., 2011). These subjective measures are critical in capturing the personal and nuanced experiences of IO. In other words, the media-centric perspective focuses on the characteristics of media, while the cognitive perspective emphasises the role of individual factors in shaping the experience of IO.

This cognitive approach aligns with the person-environment fit model, which highlights the importance of balancing personal capacities with environmental demands (Cooper et al., 2013). It also complements the Transactional Theory of Stress, which examines the dynamic process of stress development. By integrating insights from both frameworks, this research seeks to offer a deeper understanding of IO, providing a comprehensive perspective on how individuals navigate and cope with the challenges posed by DLTs.

4.3.1 The Person-Environment Fit Model

The Person-Environment (P-E) fit model of stress is a widely used model in stress and overload research (Ayyagari et al., 2011; Biggs et al., 2017; Cooper et al., 2001; Lee et al., 2016a). The P-E fit model suggests an equilibrium relationship between individuals and their environment (Cooper et al., 2013; Edwards et al., 2006). When there is a lack of fit between individuals' values and their environment, it can result in unmet needs and demands that lead to overload (Cooper et al., 2001). In other words, overload arises from an imbalance between environmental demands and a person's ability to cope with those demands (Shi et al., 2020; Yu et al., 2019). In an examination of the literature on P-E fit, Cooper et al. (2013) stated that this discrepancy can manifest in two distinct ways, as shown in Figure 4.1. A misfit can occur between an individual's values and the environmental resources, or between an individual's abilities and the environment's demands (Ayyagari et al., 2011; Kristof-Brown et al., 2005). The fit approach helps assess the perceived discrepancy between what an individual wants and what their job provides, or how well their needs are met by their job. In examining research on the literature on P-E fit, Cooper et al. (2013) identified two main types of misfit. The first occurs when there is a discrepancy between an individual's values and the environmental resources available to satisfy those values. Values often mirror an individual's conscious desires, encompassing their preferences, motives, and goals (Ayyagari et al., 2011; Cooper et al., 2013). When there is a disconnect between how individuals subjectively evaluate the resources provided by their environment and those they perceive that they need to achieve their goals, this can lead to stress. This approach is utilised to evaluate the perceived gap between what students desire in their learning experiences and what their DLTs provide (Al Abdullateef et al., 2021; Lee et al., 2016a). The second type of misfit arises between an individual's abilities and the demands imposed by their environment. Abilities encompass various factors such as skills, knowledge, time, and energy, while demands refer to an individual's subjective assessment of the requirements they face (see table 4.1). This means that the same set of requirements can be perceived as different demands by different individuals. It is essential to recognise that values-supplies fit and abilities-demands fit provide two complementary viewpoints (Ayyagari et al., 2011) that collectively demonstrate how well individuals and their environments meet each other's needs (Cooper et al., 2013; Edwards et al., 2006). Due to its wide-ranging relevance across various settings, the P-E fit model aligns especially well with the transactional perspective of stress, which is discussed next in the section. This synergy arises because both frameworks emphasise the dynamic interaction between individuals and their environments, highlighting how personal characteristics and external demands shape stress responses. The P-E fit model, by focusing on the congruence between individual needs and environmental factors, complements the transactional view's emphasis on the continuous process of appraisal, adaptation, and coping in response to stressors.

Table 4.1: Versions of person-environment fit (Adopted from Cooper et al. (2013))

Type of Misfit	Focus
Supplies-Values Fit	Misfit between environmental supplies and personal motives, goals, and values
Demands-Abilities Fit	Misfit between environmental demands and personal skills, knowledge, and abilities

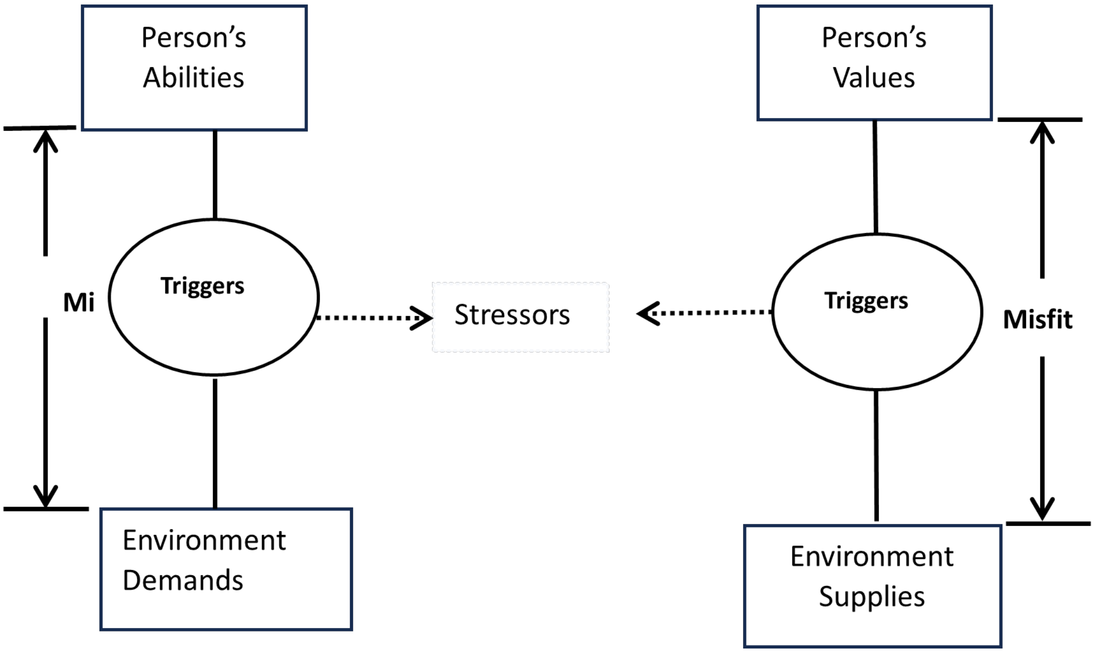


Figure 4.1: Diagram illustrating the Person–Environment Fit Model

4.3.2 Transactional-Based Theory of Stress: Stressors, Strain, and Outcome

The Transactional-Based Theory of Stress (TBTOS) is a theory within social psychology that is utilised to examine the causal links between stressors, as demonstrated in numerous previous successful studies on overload (Fu et al., 2020; Lee et al., 2016a; Shi et al., 2020; Yu et al., 2019; Zhang et al., 2022a). TBTOS draws upon the theory of P-E fit as its foundation (Cooper et al., 2013; Lee et al., 2016a). For instance, Al Abdullateef et al. (2021) conducted a study examining the transaction-based approach to stress induced by DLTs (e.g., WhatsApp). They defined "stress" as a state experienced by an individual when faced with an environmental situation perceived as presenting a demand that threatens to exceed the individual's capabilities and resources for meeting it, thereby threatening their well-being (Al Abdullateef et al., 2021, p. 3) . The transaction-based approach elucidates stress as a dynamic interaction, or transaction, between what is referred to as a 'stimulating condition' on one hand, and the individual's reaction to it on the other (see Figure 4.2). In this context, stress is characterised as a transactional process in which *stressors* are the stimuli that individuals encounter, and *strain* is the individual's response to these stressors, for example, students' feelings of digital fatigue in the context of DLTs. Strain can lead to consequences, usually referred to as *outcomes* (Cooper et al., 2013). For example, students' perceived academic performance is a pertinent outcome in the context of this research (see Figure 4.2).

The appraisal process focuses on the individual's subjective interpretation of a situation rather than the objective circumstances. This perspective recognises that external factors, including interpersonal interactions and the surrounding environment influence stressors. Within the realm of DLTs, students' interactions with peers and posts can either contribute to distractions or offer valuable support, affecting how they cope with stress. A key factor in this dynamic is technology self-efficacy—students' confidence in their ability to navigate DLTs—which acts as a moderating influence. In this research, the role of technology self-efficacy as a moderator is explored in greater detail within the research model development section.

Table 4.2: Description of transactional process concepts (Adopted from Ayyagari et al. (2011))

Concept	Definition
Stressors	Conditions (triggers) that a person encounters in his or her environment
Strain	The emotional and behavioural reactions a person has in answer to stressors
Outcome	Effects of strain, impacting the personal level

Given its broad applicability across different contexts, the P-E fit model is particularly synergistic with the transactional view of stress. This synergy enables a deeper understanding of how stressors interact with individuals' perceptions and responses. A visual representation of the integrated theoretical framework central to this study's approach is presented in Figure 4.3. Therefore, this research adopts an integrated theoretical framework combining the P-E fit model and the transactional view of stress to explore the dynamics of stress within the context of DLTs.

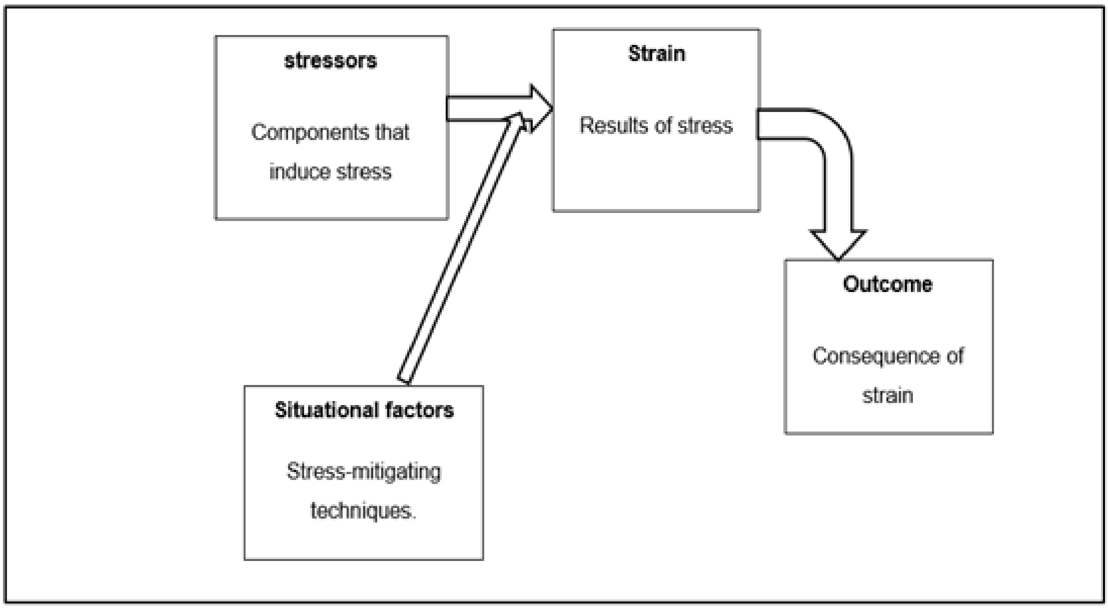


Figure 4.2: Diagram illustrating the Transactional-Based Theory of Stress

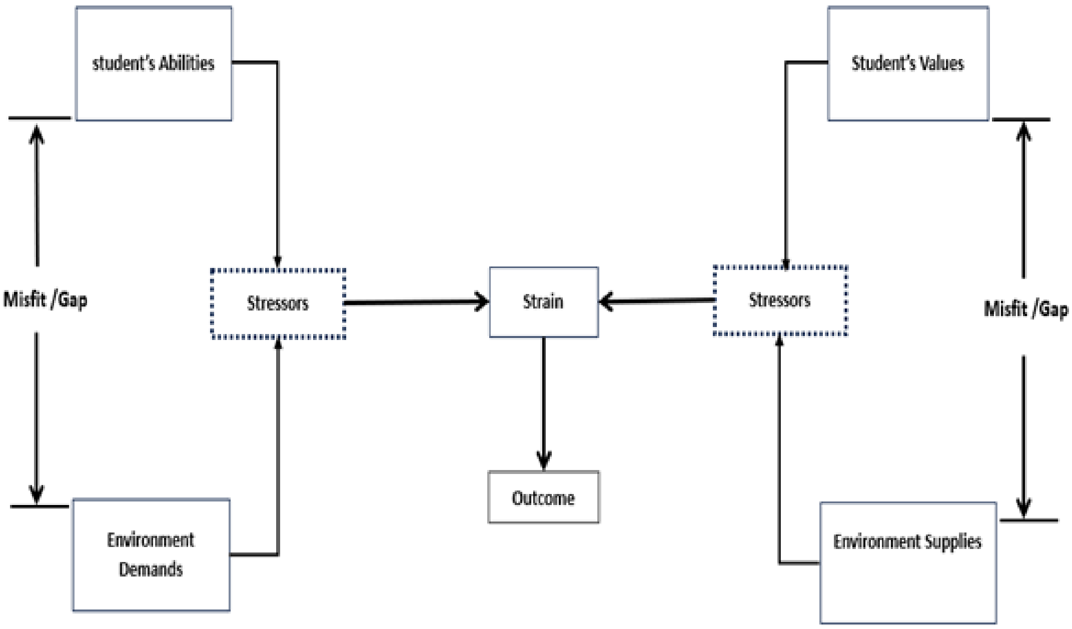


Figure 4.3: Integrated conceptual model combining Person–Environment Fit and Transactional-Based Theory of Stress

4.3.3 Rationale for Theoretical Selection

In developing the model for this research, I drew upon both the P–E Fit model and the TBTOS because each framework addresses complementary aspects of the stress process. Prior studies that applied TBTOS in the context of overload primarily focused on three core components—stressors, strain, and outcome (Al Abdullateef et al., 2021; Alvarez-Risco et al., 2021; Xiao and Mou, 2019; Yu et al., 2019). However, they largely overlooked the role of triggers that initiate stress appraisal. Conversely,Lee et al. (2016a) combined both P–E Fit and TBTOS, incorporating triggers, stressors, and strain, but did not extend the model to examine outcomes. Building on these gaps, the present research integrates both theories in order to capture a more complete process: from the emergence of triggers, through stressors and strain, to eventual outcomes. This progression provided the rationale for selecting and combining the two theoretical perspectives in model development.

4.4 Identifying Stressors, Strain, and Outcome Sources Derived From Existing Literature

In digital learning environments, tools such as online forums, SNS, and emails play a crucial role in fostering engagement and interaction. These tools provide continuous connectivity, facilitating educational activities and keeping students connected to abundant sources of information (Al Abdullateef et al., 2021; Conrad et al., 2022; Fakhfakh and Bouaziz, 2022; Lee et al., 2016a). However, this constant connectivity can lead to overload, where students experience stress from feeling overstimulated and overwhelmed by external demands (Cooper et al., 2013).

The literature demonstrates broad consensus on the impact of information and communications technology (ICT)-induced overload, encompassing stressors and strains (Table 4.3). However, scholars vary in their interpretations and classifications of the different types of overload. For example, ICT-induced overload has been categorised into three main types: information overload, system feature overload, and communication overload

(Karr-Wisniewski and Lu, 2010). However, these early frameworks neglected to address the more recent issue of social overload, which was later introduced by Maier et al. (2015b).

Social overload is recognised as a newer phenomenon (Zhang et al., 2016). It refers to the negative effects caused by excessive engagement on social networking sites. Expanding on earlier research (Karr-Wisniewski and Lu, 2010; Maier et al., 2012), scholars have examined overload as a set of stressors that often contribute to increased stress levels (Fakhfakh and Bouaziz, 2022; Fu et al., 2020; Lee et al., 2016a; Shi et al., 2020; Yu et al., 2019). Additionally, specific ICT characteristics are closely tied to communication and information overload (Lee et al., 2016a; Lim et al., 2017; Maier et al., 2015b).
Given the variety of these dimensions of overload identified in the IS literature, all of which are used interchangeably with or closely linked to IO (Bawden and Robinson, 2020; Belabbes et al., 2023). For this reason, this research suggests that adopting a single, rigid definition would inadequately capture its intricacies. Attempts to frame IO using a narrow set of necessary and sufficient criteria oversimplify this highly nuanced concept. A more flexible and comprehensive approach is essential to encompass the diverse experiences and features associated with IO in the context of DLTs. However, to develop a more thorough and flexible concept, it is essential first to examine the core concepts. Below, four major dimensions of IO are presented: content overload, communication overload, social overload, and system features overload.

4.4.1 Content Overload

In academic contexts, students encounter a constant influx of information from DLTs, delivered through videos, readings, discussion boards, emails, and notifications. One key dimension of information overload in these environments is content overload. Content overload refers to the subjective experience of feeling overwhelmed when a student encounters an excessive amount of information that exceeds their capacity to process within the available time and cognitive resources (Eppler and Mengis, 2008; Karr-Wisniewski and Lu, 2010). This subjective experience aligns with findings from information retrieval and neuro-information science, where users' limited cognitive resources, combined with complex information environments, have been shown to drive overload, strain, and sub-optimal decision making during search and evaluation tasks (Belabbes et al., 2023; Moshfeghi et al., 2013, 2016; Pinkosova et al., 2020).

4.4.2 Communication Overload

Communication overload refers to the feeling of being overwhelmed when multiple communication channels—such as emails, messaging apps, and social media—demand simultaneous attention (Karr-Wisniewski and Lu, 2010). They studied communication overload within workplace environments and found that constant interruptions from different communication streams significantly hindered employees' ability to focus, leading to stress and reduced performance. In educational settings, DLTs with embedded communication channels, such as email, forums, and messaging apps, can easily overwhelm students. Jackson and Farzaneh (2012) similarly highlighted that communication overload leads to IO, impairing learning and information retention.

4.4.3 Social Overload

Social overload arises from excessive engagement in social interactions, particularly in online environments such as SNS, online forums, and collaborative platforms. Such contexts within DLTs can often push students beyond their capacity for social interaction (Maier et al., 2015b). They explored social overload and found that constant pressure to engage in social interactions on platforms such as SNS caused stress and anxiety. They suggested that users can feel overwhelmed by the social expectations associated with maintaining a constant online presence, a dynamic that easily translates into educational platforms where group work and forum discussions are integral parts of the learning process.

4.4.4 System Features Overload

System features overload arises when the demands of utilising various tool features surpass users' ability to manage them effectively (Karr-Wisniewski and Lu, 2010). When DLTs (e.g., SNS) offer numerous features or functions that require significant mental effort to navigate, users can experience system features overload (Fu et al., 2020; Sheng et al., 2023). Lee et al. (2016a) identified system features overload as one of the leading causes of fatigue in users, particularly when there is an expectation to use and adapt to new features frequently. This overload often leads to frustration and disengagement, as users struggle to balance their learning tasks with managing the intricacies of the tools.

4.4.5 Original Conceptualisation in This Research

While classical definitions provide clarity, no single definition fully captures the complexity and nuances of IO in digital learning environments. Previous attempts to develop an integrative framework for IO have not adequately addressed its heterogeneous nature. In this context, heterogeneity refers to two aspects: (1) the interchangeable terminology used in the literature—such as "information overload," "communication overload," and "cognitive overload"—which reflects a lack of consensus on a unified definition; and (2) the conceptual diversity of IO, which encompasses multiple dimensions with overlapping and distinct characteristics, including content, communication, social, and system features overload.

Recognising this heterogeneity, the present research adopts a new perspective: conceptualising IO as a multifaceted and fluid construct rather than a singular phenomenon. This approach acknowledges that these dimensions rarely occur in isolation; instead, they interact dynamically and often amplify one another. For example, a student using both a learning management system (LMS) and social networking sites (SNS) may simultaneously experience content overload from an abundance of resources, communication overload from frequent notifications, system features overload due to complex functionalities, and social overload arising from group work and peer interactions (see figure 4.4). Understanding these dimensions as interrelated aspects of IO is crucial, as one type of overload can often amplify or trigger others.

As derived from the literature, previous studies (4.3) demonstrate a widespread agreement among researchers that strain arises in response to stressors, often presenting in the context of DLTs as feeling exhaustion (Al Abdullateef et al., 2021; Cao and Sun, 2018; Shi et al., 2020; Yu et al., 2019) or SNS fatigue (Fu et al., 2020; Islam et al., 2018; Lee et al., 2016a; Yu et al., 2018). Fatigue is typically characterised by feelings of tiredness, low energy, or exhaustion (Lee et al., 2016a). In this research, the term 'digital fatigue' is utilised as the concept of strain, referring to a feeling of exhaustion from prolonged screen exposure (Romero-Rodríguez et al., 2023). This term encompasses a broader range of factors relevant to DLTs.

Furthermore, the outcome of strain has been demonstrated to ultimately lead to discontinuous use (Cao and Sun, 2018; Fu et al., 2020; Maier et al., 2015a) or perceived academic performance issues on platforms like WhatsApp (Al Abdullateef et al., 2021; Shi et al., 2020) and SNS (Yu et al., 2019).
In this research, the focus is on the behavioural outcome of perceived academic performance in the context of DLTs, which refers to a student's subjective evaluation of their academic achievement, considering their attitudes, abilities, effort, and accomplishments as reflected in their grades (Cruz et al., 2024). Perceived academic performance was selected as an outcome construct because it reflects students' subjective assessments of their academic success, which overload and strain caused by DLTs can influence. Prior research has shown that overload and emotional strain, such as fatigue and stress from excessive information or communication demands, negatively affect students' motivation and engagement, ultimately leading to lower perceived academic performance (Al Abdullateef et al., 2021).

Expanding upon previous research, this study proposes that DLTs can exacerbate the P-E misfit by increasing the gap between individuals' abilities and the demands placed on them, as well as between their values and the resources available. The following section identifies the specific DLT characteristics used in this research.

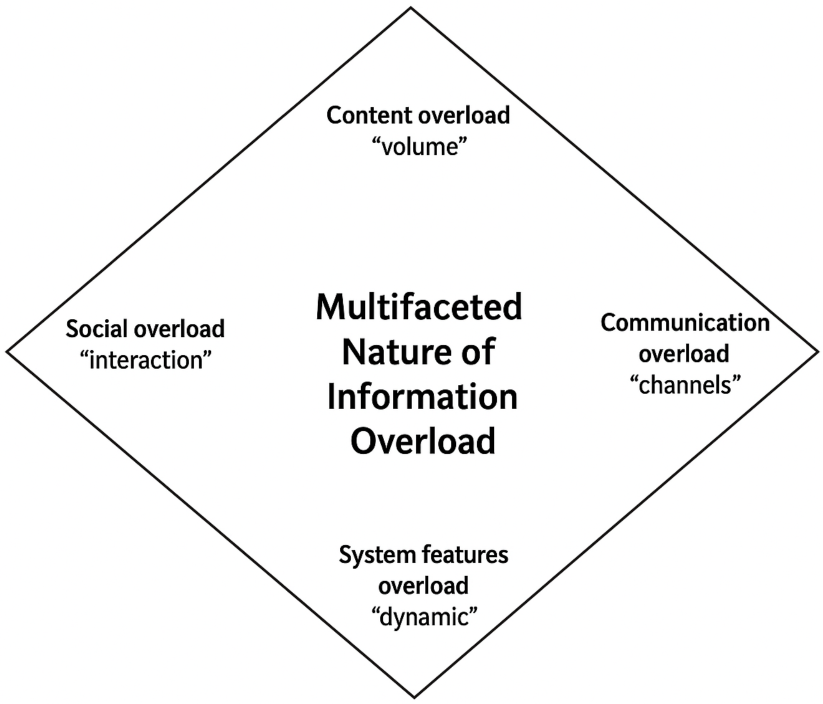


Figure 4.4: Illustration of the multidimensional structure of information overload

Table 4.3: Prior studies on overload in digital learning tools

Authors	Stressor	Strain	Outcomes	Theoretical Background
Lee et al. (2016a)	-Information overload -Communication overload -System features overload	SNS fatigue	-	Person-Environment Fit Model of Stress -Transactional Model
Fu et al. (2020)	-Information overload -Communication overload -System features overload	Social media exhaustion	Discontinuous usage	Transactional Model
Shi et al. (2020)	-Information overload -Communication overload -System features overload	-Technostress -Exhaustion	Academic performance	Transactional Model
Al Abdullateef et al. (2021)	Information overload, Communication overload, Invasion of life, Invasion of privacy	Fatigue	Perceived performance	Transactional Model
Yen (2022)	-Information overload -Communication overload -System Features overload	Work stress	-	Stimuli-Organism-Response Model
Alvarez-Risco et al. (2021)	Communication overload, Social overload	Technostress, Exhaustion	Academic performance	Transactional Model
Maier et al. (2012)	Social overload	Emotional exhaustion	Satisfaction, Discontinuous usage intention	SSO Model
Zhang et al. (2016)	Information overload, Communication overload, System features overload	Social network fatigue, Dissatisfaction	Discontinuous usage intention	Transactional Model
Whelan et al. (2020)	Boredom proneness, Information overload, Communication overload	Social Media Fatigue	Transactional Model	-
Cao and Sun (2018)	Information overload, Communication overload, System features overload	Exhaustion, Regret	Discontinuous intention	Stimuli-Organism-Response Model
Yu et al. (2019)	-Information overload -Communication overload	Technostress, Exhaustion	Academic performance	Transactional Model
Islam et al. (2021)	-Information overload -Communication overload	SNS fatigue	-	Transactional Model
Fakhfakh and Bouaziz (2022)	-Information overload -Communication overload -Social overload	Work overload -Dissatisfaction towards SNS	-Job performance -Discontinuous intention	Transactional Model
Shi et al. (2020)	-Information overload -Communication overload -Social overload	Social media exhaustion	academic performance	Transactional Model
(Eliyana et al., 2020)	-Information overload -Communication overload -Social overload	Social media exhaustion	Job performance	-

4.5 Identifying Characteristics of DLTs

To identify the characteristics of DLTs that contribute to IO, the research followed the procedure described in this section. First, a review of existing studies on IO and technology-induced stress was conducted to identify recurring concepts deemed causative, which are categorised as triggers in this research. The resulting characteristics, along with their definitions, illustrative technologies, and references, are presented in Table 4.5.

Given that information volume, irrelevance, and equivocality refer to the informational dimension of DLTs, these are categorised as *information characteristics* Lee et al. (2016a). The features of hyperconnectivity and interruptions highlight the flow of communication and are therefore classified as *communication characteristics.* Additionally, excessive interaction pertains to the interactive activities present in DLTs, thus classifying it as a *social characteristic.* Lastly, the pace of change and complexity underscores and uses the evolving landscape of DLTs and are categorised as *dynamic characteristics.*

Table 4.5: Characteristics of Digital Learning Tools with Definitions

Sources	**DLTs Characteristics Identified**	**Definition**
Chen et al. (2012)	Information volume	The degree to which the amount of data, and content that students are exposed to within DLTs, such as SNS, online forums, and emails.
Guo et al. (2020)	Information irrelevance	The degree to which the information available on DLTs is unaligned with a student's specific needs.
Lee et al. (2016a)	Information equivocality	The degree to which information equivocality arises from DLTs in ambiguous situations with multiple, conflicting views among stakeholders.
Fredette et al. (2012)	Hypeconnectivity	The degree to which DLTs are constantly connected, easily reachable, and immersed in a networked environment that offers abundant information, interactivity, and the capability to record and preserve personal experiences.
Rennecker and Godwin (2005)	Interruption	The degree to which an unscheduled, real-time interaction that is not initiated by the recipient causes them to interrupt their ongoing activity
Boon (2016)	Excessive interaction	The degree to which the amount of interactions exceeds a student's ability to effectively participate OR the degree to which highly interactive activities exceed a student's ability to effectively participate, such as comments, chatting, reading conversations, voting, and tagging
Lee et al. (2016a)	Pace of change	The degree to which a student perceives DLTs alteration as occurring quickly
Ayyagari et al. (2011)	Complexity	The degree to which of effort needed to utilise the DLTs

4.5.1 Theoretical Framing of the research

This section outlines the key insights from this chapter, which are crucial for developing the theoretical model presented in the next section. These insights include:

1. Viewing IO as a multifaceted and fluid construct that encompasses a variety of constructs with both common and distinct features.

2. Modern perspectives on stress-related overload emphasise the individual, proposing that overload emerges not solely from individual or environmental factors but from the dynamic interaction between them.

3. The Person-Environment Fit model offers a framework for understanding the dynamics of person-environment fit. In this model, the fit is assessed across two dimensions: (i) the alignment between individual abilities and environmental de-

mands, and (ii) the alignment between individual values and environmental supplies. A mismatch in either dimension has been shown to contribute to strain.

4. The diverse and interchangeable terminology used in current IO research indicates that a novel approach is needed to effectively conceptualise the phenomenon.

5. A review of existing IO literature has identified the multifaceted nature of IO, encompassing content overload, communication overload, social overload, and system features overload. These factors are recognised as potential stressors within the context of the present research.

4.6 Theoretical Framework and Hypothesis Development

Drawing from the stress perspectives outlined in the P-E fit model and TBTOS, as analysed above, this research's research model was developed consisting of four distinct sets of components (see figure 4.5): (a) DLTs characteristics, acting as triggers to overload and potentially leading to a P-E misfit; (b) dimensions of IO, functioning as stressors; (c) digital fatigue, which serves as strain; and (d) perceived academic performance as an outcome.

4.6.1 Triggers and Stressors

This section outlines the core elements of the conceptual framework—triggers and stressors—that inform hypothesis development. Triggers are characteristics of DLTs that initiate IO, acting as environmental stimuli that increase cognitive demands. Stressors are the resulting IO manifestations, such as content, communication, social, and system feature overload. The following subsections (4.6.2 - 4.6.5) examine these triggers across four streams: information, communication, engagement, and dynamic characteristics

4.6.2 Characteristics from 'Information' Stream – Volume, Irrelevance, and Equivocality

With the integration of multimedia elements, interactive features, and online resources, educational technology has expanded the range and quantity of information available to learners (Chen et al., 2011; Mayer and Moreno, 2003; Shrivastav and Hiltz, 2013) are among the studies that have explored the rise of IO in the context of educational technology. They have highlighted the challenges learners face when they encounter an overwhelming amount of information that exceeds their cognitive processing capabilities. Consider the case of Taylor, a hypothetical university student who adopts a variety of DLTs and educational resources to enrich their learning journey. These tools encompass email, recorded video lectures, LMS, collaboration tools, SNSs, engaging online forums, and instant messaging applications. Within Taylor's academic realm, voluminous information abounds via various channels. For instance, their inbox is inundated with messages from instructors and fellow students, recorded video lectures await review, the LMS hosts a multitude of assignments and readings, collaboration tools foster group activities, SNSs and forums encourage lively discussions, and instant messaging apps facilitate real-time communication. Navigating this extensive array of digital resources presents a daily challenge for Taylor, necessitating effective task prioritisation and information volume management. Nevertheless, the sheer diversity and volume of digital tools often prove overwhelming, which may result in Taylor suffering from content overload. Chen et al. (2011) also investigated the impact of multimedia presentations on content load, and their findings emphasise the importance of managing cognitive load by designing educational materials that appropriately balance the use of multimedia elements and instructional strategies. When the content load exceeds the learner's capacity, it can impede the learning process and hinder the acquisition of new knowledge and skills. In other words, it can be assumed that a significant volume of information beyond a certain learner capacity axiomatically leads to and exacerbates content overload, and numerous studies have observed moderate to strong positive associations between the quantity of information and the occurrence of content overload (Brown et al., 2014; Chen et al., 2009; Graf and Antoni, 2021). In terms of P-E fit, exposure to higher information volume on a frequent basis can lead to two types of P-E misfits for students. The first type is an imbalance between the resources available in the learning environment and the student's personal motives, goals, and values. The other is a mismatch between the demands placed on the student by the learning environment and their individual skills and abilities (Cooper et al., 2013; Edwards, 1991). Consequently, as the level of information volume increases, it leads to a greater P-E misfit, resulting in higher levels of content overload experienced by students when using DLTs. Accordingly, the following hypothesis is proposed:

H1a: *Students' perception of information volume will be positively related to content overload when using DLTs.*

The literature has extensively focused on the concept of 'relevance', which is considered a significant dimension of information quality (Graf and Antoni, 2021; Guo et al., 2020; Lee et al., 2016a). Indeed, it has been recognised as the core concept of information science itself, since the emergence of the discipline during the 1940s and early 1950s; however, despite such longstanding interest, there is no universally accepted definition of the concept (Graf and Antoni, 2021). This reflects that relevance is, in fact, a multidimensional and sophisticated cognitive concept that depends heavily on how information users perceive it and their specific information needs (Schamber et al., 1990). It is a dynamic appraisal that is contingent upon users' assessments of how well information aligns with their needs at a given moment. The usability of information is also associated with its benefit to the user. The converse, information *irrelevance*, refers to the degree to which the information available on DLTs is irrelevant, unimportant, trivial, and not applicable to the specific needs of a user in the context of DLTs (Guo et al., 2020). If information is deemed irrelevant, it may necessitate further clarification, leading to increased effort and IO for the user (Lampe et al., 2011). According to Ackoff (1967), even before the digital age, individuals received more information than they could digest, even if they spent all their time trying to do so. This leads to IO and requires them to spend a great deal of time separating the relevant from the irrelevant and searching for the kernels in the relevant information. To take a hypothetical example, Amy is a university student who relies heavily on DLTs to support her education. Despite the advantages of these digital tools, Amy grapples with the challenge of relevance. Sometimes, the information she encounters within these tools does not align with her specific needs or the context of her studies (e.g., course content). She finds irrelevant messages, non-essential materials, or trivial discussions that do not contribute to her learning objectives. This irrelevant information requires Amy to sift through it to find the relevant content. This additional effort requirement can lead to content overload and thus negatively affect her learning experience, disrupting her focus and hindering her ability to concentrate on the core learning materials. In the context of P-E misfit, information irrelevance arises when DLTs deliver content that doesn't align with Amy's expectations of its significance in their learning journey. Consequently, a higher degree of information irrelevance can result in a misalignment between Amy's abilities and the demands placed on them within the digital learning environment, contributing to elevated levels of content overload. A study by Kushnir (2009) focused on identifying factors that contribute to students' perceptions of overload. The results indicated that students with extensive experience with online learning technologies were negatively affected in their learning when exposed to excessively busy online environments that contained irrelevant information. The study highlighted that online environments often present a large volume of information and stimuli (indeed, they are typically designed and sold on the premise that they do so), some of which may be irrelevant and distracting. The way students handle such irrelevant or distracting information and stimuli can significantly influence their learning outcomes. In other words, in the context of this research, information irrelevance arises when the information delivered by DLTs does not align with users' initial expectations regarding its relevance and significance in assisting their learning process. Thus, when information irrelevance is higher, this leads to a greater mismatch between a student's abilities and the demands placed on them, resulting in greater P-E misfit and higher levels of content overload when using DLTs. Accordingly, the following hypothesis is proposed:

H1b: *Students' perception of information irrelevance will be positively related to content overload when using DLTs.*

Information equivocality is another characteristic that emerges in unclear contexts where stakeholders hold various, opposing perspectives (Kydd, 1989). High-level equivocality leads to confusion and limits an individual's ability to form a coherent understanding (Grover et al., 2006; Kydd, 1989). It refers to situations in which clarity and understanding are lacking, leading to uncertainty and difficulties in interpreting information (Grover et al., 2006). In this context of DLTs, despite the presence of information, students can struggle to cope with its uncertainty and lack of clarity (Grover et al., 2006; Lee et al., 2016a). For example, John is a university student taking a course on artificial intelligence. John relies heavily on DLTs and encounters numerous resources on neural networks. He watches video lectures, reads articles, and participates in online discussions. However, he notices differing viewpoints and approaches presented across these materials. Some sources emphasise the mathematical aspects, while others focus on practical applications. Because of the varying perspectives and approaches, John finds it challenging to form a coherent understanding of neural networks. He often feels uncertain about which concepts to prioritise and how to apply them in real-world scenarios. To resolve his confusion, John engages in extensive research and communication. He watches additional videos, reads supplementary articles, and participates in discussion forums. As a result, he has so much information on neural networks that it becomes overwhelming. He struggles to manage his time effectively and becomes stressed as a result. Thus, John's efforts to clarify his understanding may be hindered by content overload. In sum, the conflicting information and diverse perspectives he encountered created equivocality, which, in turn, drove him to seek more information. This quest for clarity ultimately resulted in content overload. The meta-analysis by Graf and Antoni (2021) shows that content ambiguity impairs information processing and understanding, thereby contributing significantly to IO (Graf and Antoni, 2021). In other words, as information equivocality rises, so does the likelihood of experiencing content overload. In the literature examining students' use of DLTs (e.g., SNS), empirical evidence indicates that IO is positively correlated with information equivocality (Lee et al., 2016a). When the meaning of information received via DLTs (e.g., e-mail and instant messaging from video conferencing tools) is highly equivocal, students often need to engage in additional information exchange to clarify its meaning, depending on the extent to which the information has multiple meanings and can be understood from diverse perspectives. Consequently, as equivocal messages are encountered more frequently, the likelihood of experiencing content overload increases. Accordingly, the following hypothesis is proposed:

H1c: *Students' perception of information equivocality will be positively related to content overload when using DLTs.*

4.6.3 Characteristics from 'Communication' Stream - Hyperconnectivity and Interruptions

Hyperconnectivity refers to the state of being constantly connected, easily reachable, and immersed in a networked environment that offers abundant information, interactivity, and the capability to record and preserve personal experiences (Fredette et al., 2012). One of the most significant effects of advancements in ICTs is arguably the increased ability of individuals to remain constantly connected (Ayyagari et al., 2011). This phenomenon, referred to as *presenteeism*, can exacerbate feelings of overload in the workplace due to constant connectivity (Ayyagari et al., 2011; Issa and Bahli, 2018). The increasing reliance on technology and hyperconnectivity has become a growing concern for productivity in various fields (Issa and Bahli, 2018; Kinman, 2019). This hyperconnectivity, facilitated by digital tools, reflects the widespread use of technology, enabling communication and access to information at any time and from anywhere. Ayyagari et al. (2011) suggests that the presence of technology can lead to task fragmentation, as individuals encounter an increasing volume of communication, often resulting in unresolved tasks. Due to the constraints of human cognitive capacity, individuals can effectively handle a certain amount of communication; however, when the volume of communication overrides this threshold, individuals experience stress (Al Abdullateef et al., 2021). Within the workplace context, the research identified the difficulties employees encounter in dealing with overload. One of the challenges highlighted is the negative consequences of internet accessibility. The constant availability of the internet enables employers to reach employees at any time and from anywhere (Ayyagari et al., 2011; Choi and Lim, 2016; Delpechitre et al., 2019). The multitude of connectivity options can cause disconnections and contribute to overload within the workplace (Karr-Wisniewski and Lu, 2010). In the context of DLTs, hyperconnectivity contributes to the abundance of readily accessible information everywhere. DLTs provide students with access to a vast amount of educational resources, online materials, interactive platforms, and communication channels. This abundance of information can be considered information-rich, a key hyperconnectivity component, as it offers a wealth of learning opportunities and resources for students to explore and utilise. However, the challenge lies in effectively managing and leveraging this abundance of information. With hyperconnectivity and the constant availability of information, individuals can potentially face IO. Content overload can occur when the volume and complexity of information received surpasses the individual's capacity to effectively process and utilise it (Eppler and Mengis, 2008). This can lead to feelings of being overwhelmed, decreased focus, and difficulty in extracting relevant and meaningful insights from the available information rise (Graf and Antoni, 2021). Hence, as the level of hyperconnectivity increases, it leads to a greater P-E misfit, resulting in higher levels of content overload that may be experienced by students when using DLTs.

On the other hand, due to their constant connectivity and engagement, students are more prone to experiencing communication overload. It has been observed that this state of hyperconnectivity can negatively affect both the performance and well-being of users, as noted by (Kolb et al., 2012). The shift towards blended learning in the post-COVID-19 era has heightened students' dependence on DLTs, often creating an expectation of frequent availability, even when students may not be in optimal conditions or require time with their families. Notably, (Xiao and Mou, 2019) found that presenteeism, the liking to be connected despite challenges, positively influences privacy invasion and encroachment on personal life. Moreover, students remain fully connected through DLTs (e.g., SNS, online forums), and the potential for collaborative learning, peer interaction, immediate feedback, and social engagement is heightened. DLTs flourish in an environment where hyperconnectivity enables effortless communication, seamless collaboration, and active engagement, thereby enhancing the learning experience with greater interactivity (Fredette et al., 2012). Nevertheless, while hyperconnectivity offers several advantages to learning, the continuous flow of interactions and engagements may also result in students experiencing overwhelm, a phenomenon referred to as 'social overload' (Maier et al., 2012, 2015b).

For example, Sarah is an enthusiastic university student who fully leverages DLTs to enhance her educational experience. Being constantly connected, she has a hub of communication in her email inbox, continually receiving messages from professors and fellow students. The LMS serves as her portal to assignments, readings, and course materials. Collaboration tools facilitate group work, SNSs and forums spark discussions, and instant messaging apps enable real-time communication. Sarah is immersed in an environment where information is abundant and accessible from anywhere, at any time. She can explore a wealth of educational resources, engage with interactive platforms, and connect with peers effortlessly. This information-rich digital learning environment, characterised by abundant resources and constant connectivity, reflects a key component of hyperconnectivity, offering Sarah numerous opportunities for learning and collaboration. However, amidst this wealth of information lies a challenge. Constant connectivity and the availability of vast amounts of information, surpassing her capacity to process and utilise it effectively, lead to Sarah being exposed to content overload. The state of constant connectivity generates demands from multiple channels via DLTs and the expectation of immediate responses, coupled with the continuous flow of messages, can be overwhelming (exceeding her capacity to handle them effectively), making her susceptible to communication overload. Easily reachable and immersed in a networked environment reflects a key component of hyperconnectivity through DLTs, creating an expectation of active engagement so Sarah actively engages within DLTs, particularly in collaborative and social learning environments. Retaining active engagement and updates at the cost of her time and effort can exacerbate the gap between perceived and actual demands, leading to stress and social overload. Given such scenarios, it can be argued that the combination of easy accessibility, information abundance, and active engagement contributes to stress arising from factors such as content overload, communication overload, and social overload. In terms of P-E fit, the hyperconnectivity demanded by DLTs can create an expectation of immediate responses, placing pressure on students to be always available and responsive. This constant stream of communication can be overwhelming and result in communication overload. Additionally, the increased demands placed on students in terms of time and effort by DLTs can exacerbate and enhance the P-E gap, leading to stress and further challenging their ability to cope with P-E fit. Accordingly, the following hypotheses are proposed:

H1d: *Students' perception of hyperconnectivity will be positively related to content overload when using DLTs.*

H2a: *Students' perception of hyperconnectivity will be positively related to communication overload when using DLTs.*

H3a: *Students' perception of hyperconnectivity will be positively related to social overload when using DLTs.*

Interruptions

An interruption is defined as "a synchronous interaction which the recipient does not initiate, is unscheduled, and results in the recipient discontinuing their current activity" (Rennecker and Godwin, 2005). Cognitive research indicates that a moderate level of interruptions can enhance performance by enhancing focus on the main task and facilitating multitasking (Karr-Wisniewski and Lu, 2010). On the other hand, in the field of human-computer literature, ICTs themselves are recognised as a potential source of interruptions. These interruptions can negatively affect efficiency and increase stress levels (McFarlane and Latorella, 2002). ICTs provide avenues for enhanced communication between individuals, which can lead to unresolved work tasks. The constant flow of communication facilitated by ICTs may lead to challenges in task completion and decision-making, potentially causing inefficiencies in work processes and reducing task accuracy (Ayyagari et al., 2011; Tarafdar et al., 2010). Digital learning environments may involve various communication channels, such as emails, instant messaging, discussion boards, and video conferencing. These channels can be sources of constant interruptions when students receive frequent and various forms of communication, such as emails or messages sent by instructors, updated announcements in the online learning system, or even reminders of the assignment deadline, which can overwhelm their communication channels and impede their ability to focus on and respond to each communication effectively (Conrad et al., 2022). For example, Emily is a university student who relies on DLTs to aid her learning. One evening, Emily was immersed in an online lecture, trying to grasp complex concepts for an upcoming exam. Just as she was getting into the flow of the lecture, her phone buzzed with an instant message notification from a classmate asking for clarification on a study topic. This unscheduled interaction initiated by her classmate disrupted Emily's current activity. Emily finds that moderate interruptions, such as those from her classmate, help her clarify some matters; however, although they enable communication and collaboration, they also introduce interruptions. Emily has experienced days when a constant stream of emails, messages from instructors, and reminders about assignment deadlines overwhelmed her. These interruptions disrupted her workflow, made task completion challenging, and increased her stress levels. Emily noticed that frequent interruptions from various DLTs, such as emails, discussion board notifications, and instant messages, created a constant buzz in her digital life. This posed challenges to her ability to concentrate and also increased her communication overload. Emily often felt overwhelmed as she tried to manage her coursework amid this barrage of notifications. Regarding P-E misfit, Emily feels that the constant interruptions do not align with her values and preferences for focused, uninterrupted learning. She values deep concentration when studying complex topics, but often faces the expectation of constant interruption in the digital learning environment, creating a gap between her abilities (learning) and the demands placed on her. Hence, frequent interruptions can disrupt a student's study routine, cause distractions, hinder concentration, and increase communication demands, ultimately contributing to overload. (Cao and Sun, 2018; Conrad et al., 2022). Therefore, interruptions can contribute to communication overload. In terms of P-E fit, as students are limited in their abilities (resources), these increased demands enhance the P-E gap. Further, students' values and preferences regarding uninterrupted learning might not be fulfilled by the expectation of constant interruption. Accordingly, the following hypothesis is proposed:

H2b: *Students' perception of interruptions will be positively related to communication overload when using DLTs.*

4.6.4 Engagement Characteristics Stream – Excessive Interactions

Users interact with DLTs (e.g., SNS, online forums) for diverse purposes, including entertainment, information-seeking, and academic tasks. Interaction patterns considered highly interactive encompass a variety of activities, such as connecting with others, creating content, sharing content, visiting profiles, leaving comments, reading comments, engaging in conversations, reading conversations, rating, or voting on posts, following updates, and tagging content (de Vries, 2003). These activities reflect the dynamic nature of DLTs. However, while providing instant gratification, this engagement may erode the user's sense of volitional control, leading to prolonged and excessive use of DLTs (Nawaz et al., 2018). In this research, social engagement refers to the interpersonal interactions and participatory activities that students undertake within DLTs that incorporate social or collaborative features. Examples include commenting on discussion threads, liking or reacting to posts, tagging peers, sharing educational content, and participating in group chats or collaborative projects. While these features aim to foster collaboration and community, they can also increase cognitive and social demands, particularly when the frequency or intensity of interactions exceeds a student's capacity to manage them effectively. For example, excessive engagement, particularly evident in DLTs such as SNS, can trigger negative perceptions, ranging from mild to severe, encompassing emotions like anxiety, depression, and boredom. These adverse outcomes primarily stem from two key factors: social overload (characterised by excessive interactions with friends, peers, and colleagues) and content overload (characterised by an inundation of undesirable information) (Nawaz et al., 2018). *Consider* the case of Kendra, a university student pursuing a degree in Computer Science, who actively engages with various DLTs to excel in her studies. Kendra's daily routine involves participating in multiple online courses, accessing learning management systems, and engaging in discussions on various academic forums. She's passionate about learning and often immerses herself in these interactions. However, as she juggles multiple subjects and forums, the sheer volume of information starts to take a toll. She finds herself constantly switching between different resources, reviewing the content of numerous posts, and engaging with queries that reflect excessive interactions. She feels that the massive influx of content exceeds her cognitive capacity to process it effectively, and she becomes overwhelmed as she tries to keep up with the vast amount, resulting in a sense of content overload. In addition to her academic commitments, Kendra is an active member of several online student groups, where she engages in both academic and social discussions. She values the connections she's made and enjoys contributing to these communities. However, as her involvement grows and social interactions consume a significant portion of her day, Kendra begins to struggle with maintaining a healthy balance between her academic responsibilities and her social engagements. This increasing demand on her time and attention contributes to a sense of social overload. P-E misfit: Kendra realises that the demands placed on her, both academically and socially, have surpassed her capacity to manage effectively. The gap between her abilities and the ever-increasing demands of her digital learning environment has widened. To be clear, the overuse of DLTs creates expectations that compel users to engage in social interactions consistently, leading to a continuous cycle of accessing their DLT accounts and encountering a barrage of social demands. This pattern can lead to social overload, which, in turn, can result in strain (Maier et al., 2012). The research underscores that social overload arises from unwarranted or extreme social interactions, subsequently contributing to strain (Maier et al., 2015b). A study by Maier et al. (2012) examined responses to social overload on SNS, revealing that excessive virtual engagement leads to negative consequences and reduced user satisfaction.

Within an educational context, we propose that excessive engagement with DLTs, such as participation in group work or online forums, can trigger both content overload and social overload. Consequently, this may lead to physical and psychological strain, a condition termed "digital fatigue" within the study. Furthermore, users employ DLTs, like SNS, to connect with virtual acquaintances across a broad spectrum of topics. SNS serve as platforms for diverse interactions, ranging from organising events (Khan and Jarvenpaa, 2010) to discussing personal matters to deliberating on seemingly trivial subjects. However, the content and nature of these interactions can shape users' perceptions, influencing whether they are viewed as contributing to social interaction overload when using SNS (Maier et al., 2015b). This becomes particularly relevant in an educational context, especially when online forum discussions primarily revolve around insignificant or uninteresting subjects, potentially fostering the perception that interactions are overwhelming. Consequently, the constant exposure to overwhelming interactions and the persistent obligation to respond to peers' expectations can exact a toll on learners, giving rise to feelings of weariness and stress associated with their digital engagements. In terms of P-T fit, as students are limited in their abilities (resources), these increased demands enhance the P-E gap. Accordingly, the following hypotheses are proposed:

H1e: *Students' perception of excessive interactions will be positively related to content overload when using DLTs.*

H3b: *Students' perception of excessive interactions will be positively associated with social overload when using DLTs.*

4.6.5 Characteristics from 'Dynamic' Stream – Pace of Change and Complexity

In the realm of DLTs, providers frequently implement updates and introduce innovative technical functionalities to improve their services (Lee et al., 2016a). Research indicates that the design intricacies of advanced technologies, such as system complexity and the pace of change, can contribute to user stress when interacting with these technologies (Ayyagari et al., 2011).

Pace of Change refers to the extent to which users perceive changes in their DLT environment as rapid (Lee et al., 2016a). Introducing new features and interfaces can pose challenges for some users in terms of learning and effective utilisation (Fu et al., 2020). Moreover, these changes can induce stress in users, leading to system feature overload (Lee et al., 2016a). For example, students can become accustomed to a particular interface and find system alterations overwhelming. Even if the updated functions and features align with user needs, they should ideally be more user-friendly compared to previous designs. Updates to DLTs that disrupt users' familiarity with the interface can evoke feelings of fatigue (Fu et al., 2020). The ongoing evolution of DLTs places demands on students to adapt, which may involve acquiring new skills or adapting to changes in functionality. Therefore, the pace of change in DLTs may contribute to system feature overload.

H4a: *Students' perception of pace of change will be positively related to system features overload when using DLTs.*

In the context of DLTs, complexity refers to the degree of effort required to use the technology and achieve desired outcomes effectively. It encompasses the perceived difficulty in understanding system functionalities, navigating interfaces, and integrating multiple features into learning tasks (Ayyagari et al., 2011). High complexity often manifests when systems include numerous interdependent features, non-intuitive workflows, or frequent updates that require additional learning.

According to the P–E fit model, complexity increases the misfit between user abilities and environmental demands, thereby elevating cognitive load and stress levels (Ayyagari et al., 2011). Users confronted with complex systems must invest additional time and mental resources to overcome knowledge barriers, which can lead to frustration and diminished perceived control.

Empirical evidence supports this view: Lee et al. (2016a)) found that system complexity significantly predicts system feature overload in social networking and learning environments. Similarly, Ayyagari (2012) demonstrated that complexity is a critical antecedent of technostress, as it amplifies the perceived effort required to complete tasks and adapt to evolving technologies. In educational contexts, students facing complex DLTs may experience heightened stress, reduced engagement, and impaired learning outcomes.

This study hypothesises that higher perceived complexity of DLTs will increase system features overload, as students expend more cognitive effort navigating and adapting to intricate functionalities.

H4b: *Students' perception of complexity will be positively related to system features overload when using DLTs.*

4.6.6 Stressors and Strain

This subsection explains the link between stressors—manifestations of information overload—and the resulting strain experienced by students. Stressors such as content, communication, social, and system feature overload represent the cognitive and emotional pressures arising from digital learning environments. Strain, conceptualised here as digital fatigue.

Content Overload and Digital Fatigue

Using DLTs can result in content overload (Chaulk and Kelly, 2011). In research on Zoom fatigue, content overload was identified as an issue (Ebardo et al., 2021). Computer conferencing communications expand with the number of participants. For example, students' class reading assignments may be blended with an online discussion board and other material (Chen et al., 2011; Vonderwell and Zachariah, 2005). Content overload occurs when individuals struggle to distinguish valuable from irrelevant information when presented with a large pool of information to complete their tasks (e.g., achieve their learning goals) (Sarabadani et al., 2018). There are several determinants of content overload that are frequently interconnected. Content overload itself is influenced by media-related variables (such as media, technological, and social demands, and information characteristics), several personal factors (such as cognitions, attitudes, levels of frustration, ICT skills, and self-efficacy), and contextual variables (such as task complexity, time restraints, and technical support)(Chen et al., 2011; Eppler and Mengis, 2008; Schmitt et al., 2018; Tarafdar et al., 2010; Zumbach and Mohraz, 2008). The consequences of content overload can manifest as internal effects, including emotional strain Belabbes et al. (2023), which affect the individual directly, and can lead to diminished learning satisfaction and achievement Green (2011), attention issuesKoltay (2017), abandonment from assignments, discontinuedSwar et al. (2017). Moreover, individuals experiencing content overload may also feel stressed, frustrated, and dissatisfied Ragu-Nathan et al. (2008), as an overabundance of digital content can swiftly push students to their cognitive processing limits and induce a sense of overwhelmLee et al. (2016a). To summarise, an overabundance of digital content can lead to content overload, adversely affecting students' behaviour, emotions, and well-being Misra and Stokols (2012); Stokols et al. (2009). Comparable relationships between high information load, cognitive strain, and emotional responses have been demonstrated in neuro-information retrieval studies, where neural and physiological measures linked to relevance, satisfaction, and information need realisation reveal how overload and task demands shape user behaviour and well-being during information seeking Moshfeghi and Pollick (2019); Moshfeghi et al. (2013); Paisalnan et al. (2023); Pinkosova et al. (2020). Accordingly, the following hypothesis is proposed:

H5a. *Students' perception of content overload will be positively related to digital fatigue when using DLTs.*

Communication Overload and Digital Fatigue

Communication overload is another manifestation discussed in the literature, which occurs when the demands of ICT channels, such as video, audio calls, emails, and instant messages, exceed students' ability to communicate (Karr-Wisniewski and Lu, 2010). Too much communication may tire, frustrate, and agitate people, as attested by empirical studies (Lee et al., 2016a). Unchecked overload might cause physical or mental difficulties. Because online learning relies heavily on computer-mediated communication, communication overload is prevalent in such learning contexts (Federman, 2019). Drawing from previous research, a significant relationship exists between communication overload and experience fatigue, which can result in more severe mental or physical health conditions (Lee et al., 2016a,b; Yu et al., 2019; Zhang et al., 2016). In the context of DLTs, instructors can contact students, update the LSM, or provide assignment reminders. Students must reprocess fundamental task data whenever their work is interrupted. Thus, university students may experience overload and technological stress due to the frequent and immediate delivery of communication messages, which can be disruptive during study hours and thus increase the difficulty they experience in concentrating on their schoolwork, thereby exacerbating fatigue (Cao and Sun, 2018; Conrad et al., 2022; Hung et al., 2015).

Modern DLTs, such as video conferencing tools and SNSs, offer a plethora of features designed to facilitate communication; however, these very features can disrupt and distract users with a barrage of message and chat requests, leading to communication overload (Cao and Sun, 2018; Lee et al., 2016a). After handling these communication demands, individuals must allocate time to regain focus on their interrupted tasks, whether it be work or learning. For university students, excessive communication interruptions can disrupt their daily learning activities, potentially leading to exhaustion and more severe physical and mental health issues (Cho et al., 2011; Xu et al., 2022). Cognitive studies have shown that a certain level of interruption can actually enhance performance by fostering an increased focus on the primary task and enabling multitasking. However, research also indicates that excessive interruptions have detrimental effects on human behaviour, including decreased recall, accuracy, and efficiency, as well as increased stress levels and, ultimately, reduced performance (Karr-Wisniewski and Lu, 2010; McFarlane and Latorella, 2002)

For example, Ali is a university student majoring in computer science. He relies heavily on DLTs for his coursework, including video conferencing tools for attending online lectures, email for communication with professors and classmates, and messaging apps for group projects. However, the constant barrage of communication demands from these DLTs overwhelms him. Ali tries to keep up with everything, but soon he finds it difficult to concentrate on his coursework amidst the constant stream of communication. He feels exhausted from trying to juggle multiple tasks and respond to messages promptly. As a result, his productivity suffers, and he struggles to focus on his assignments. It is clear from the above arguments that in the digital learning environment, students often face a constant stream of demands and interruptions from various DLTs, such as emails, notifications, and SNS messages. Managing an abundance of communication tasks may induce fatigue in students of DLTS (Zhang et al., 2016). In other words, The communication demands arising from DLTs can interfere with students' focus on their present tasks, consequently depleting the energy needed to fulfil their academic responsibilities. These negative emotions can lead to exhaustion. Accordingly, the following hypothesis is proposed:

H5b: *Students' perception of communication overload will be positively related to digital fatigue when using DLTs.*

Social Overload and Digital Fatigue

The concept of 'social overload' was coined by McCarthy and Saegert (1978), who attributed it to a sociological context to explain the phenomenon of densely populated real-world communities. This was based on research that revealed that when individuals' capacity to manage social connections and interactions is surpassed by the demands placed on them, they experience the eponymous state (Maier et al., 2012).

The notion of social overload extends to the realm of DLTs such as SNS and online forums. Here, students are required to invest time and effort to sustain connections with their peers. An example of this lies in the context of social support, where researchers have broadened the scope of social overload to encompass the sensation that social media users may experience when they feel they are excessively providing support to others (Maier et al., 2015b). Simultaneously, interactivity remains critical in virtual communities (Maier et al., 2012). In these communities, social interaction is often characterised as 'frequent interaction among members'. Moreover, the definition of social interaction underscores communication among two or more human beings rather than interactions between humans and computers (de Vries, 2003).

In the context of DLTs, social overload refers to the subjective feeling of being overwhelmed when the level of social interaction (e.g., via SNS, online forums, or group work) exceeds a student's ability to manage it effectively. This may include activities such as group work, peer interactions on forums, in virtual networks. The increased active involvement in these social interactions can lead to an overwhelming experience, affecting students' ability to manage their learning tasks (Maier et al., 2015b). Social overload has been broadened to encompass the sensation experienced by social media users when they believe they are offering an excessive amount of social support to others (Fu et al., 2020; Maier et al., 2012). However, in this study, the primary focus is on the association with engaging in social interactions rather than on providing support to one another. Students may face the challenge of managing their time and cognitive resources to engage in group work, communicate with peers on forums, or collaborate within virtual networks. If these engagements exceed their ability to interact effectively, a feeling of overload may arise. Numerous studies have consistently shown that social overload has a notable effect on fatigue. For instance, research conducted by (Maier et al., 2015b) shows that exceeding an optimal level of SNS use has been linked to SNS exhaustion, (Zhang et al., 2016) social network fatigue, (Choi and Lim, 2016), and reduced performance (Fu et al., 2020), all demonstrating a positive correlation between social overload and exhaustion. Consider the case of Alex, a university student majoring in Psychology. Alex is passionate about her studies and actively participates in online discussions and group projects facilitated by DLTs, including SNS and online forums. As the semester progresses, Alex becomes deeply involved in various academic forums and SNS groups. She enjoys intellectual discussions with peers, but the constant flow of messages, posts, and discussions starts to overwhelm her. Alex is juggling multiple group projects, responding to numerous forum threads, and connecting with classmates on SNS. She wants to maintain these valuable connections, but it becomes increasingly challenging to keep up. Thus, the feeling of social overload creeps in as the effort required to maintain these social interactions exceeds Alex's ability to interact. While she genuinely enjoys engaging with their peers, the sheer volume of interactions, coupled with her academic workload, leads to a sense of being overwhelmed. Digital fatigue (i.e., mental and emotional strain) arises over time, as the constant engagement with DLTs and the maintenance of social interactions surpass Alex's ability to interact. This starts to affect Alex's well-being seriously. Additionally, the emotional strain becomes evident as she feels pressure to respond to messages promptly, contribute to discussions, and keep up with coursework. Additionally, studies have confirmed the association between social media overload and feelings of fatigue(Cao and Sun, 2018). Therefore, the overwhelming exposure to engagement and the continuous pressure to meet the expectations of peers can negatively impact learners, resulting in feelings of fatigue and stress arising from their DLTs engagements. Accordingly, the following hypothesis is proposed:

H5c: *Students' perception of social overload will be positively related to digital fatigue when using DLTs.*

System Features Overload and Digital Fatigue

The term 'system feature overload' refers to the situation in which users of DLTs are required to use system functionalities that are beyond their capacity to manage (Karr-Wisniewski and Lu, 2010). The key concept is that a particular technology must be tailored to the task to provide benefits to the user. Adding a new feature raises the marginal usefulness of a software product to a point, after which the software package becomes too complex, and an extra feature will drown out current program usability, even resulting in a decrease in end-user productivity (Hsi and Potts, 2000; Karr-Wisniewski and Lu, 2010). While the features of the SNS system can improve SNS utilisation, users may become overwhelmed by the system's complexity if they are required to navigate large variations in its operation. Past research has shown that before using a software package, users prefer capabilities over usability, but that these sophisticated products can lead to 'feature fatigue' over the long term. As a result, both software producers and end users might profit from more specialised packages, with fewer functionalities (Thompson et al., 2005). Technostress refers to the stress experienced by individuals due to their inability to cope with the demands of ICT in a healthy manner (Ayyagari et al., 2011). It arises when the requirements of technology use exceed an individual's coping resources, leading to psychological strain (Tarafdar et al., 2015). Researchers found that the technical difficulty of using programs or tools (i.e., the amount of work required) might lead to technostress in online learning, because of how much effort it takes to run the system (Ayyagari et al., 2011; Tarafdar et al., 2007). As a result of increased technical complexity and resulting technology weariness, users may experience a sense of feature overload (Karr-Wisniewski and Lu, 2010; Lee et al., 2016a). Students' views on technology can significantly affect the success of online learning courses (Šumak et al., 2011). Students who are more comfortable with technology are more inclined to accept online learning. When implementing new technologies, it is crucial to tailor them to the intended task to maximise their advantages. While adding more features may initially increase the utility of a technology, there comes a point where excessive complexity outweighs the benefits, leading to diminishing returns and reduced effectiveness (Hsi and Potts, 2000). Several empirical studies have confirmed that an overload of system features leads to a significant increase in user fatigue (Fu et al., 2020; Lee et al., 2016a; Li et al., 2014). In the context of education, ICT is frequently updated, and newly added functionalities following upgrades often make users uncomfortable with the new features, leading to function overload. Therefore, when students are faced with system feature overload-induced ICT, their stress levels may increase, leading to fatigue. Accordingly, the following hypothesis is proposed:

H5d: *Students' perception of system features overload will be positively related to digital fatigue when using DLTs.*

4.6.7 Moderation Relationship

Self-efficacy refers to an individual's belief in their ability to succeed in a specific task (Bandura, 1977). When applied to technology, self-efficacy refers to the extent to which an individual believes they can effectively use technology to accomplish desired tasks (Gelbrich and Sattler, 2014). This concept focuses not on the skills one possesses but on the evaluations and judgments of what one can accomplish with those skills. A study's results indicate a moderating effect on the relationship between technology overload, effort in using technology, and performance (Delpechitre et al., 2019). Considering technology self-efficacy, which plays a crucial role in shaping how students perceive and respond to IO in digital learning environments. By bolstering students' technology self-efficacy, educators and institutions can potentially reduce the negative impact of IO on digital fatigue, ultimately fostering a more productive and positive learning experience. Accordingly, the following hypothesis is proposed:

H6 *Student's technology self-efficacy has a moderating effect on the relationship between IO manifestations (system features, content, social, and communication overload) and students' digital fatigue, such that the self-efficacy would dampen the relationship between IO manifestations and students' digital fatigue.*

4.6.8 Strain and Outcome

As explained previously, digital fatigue essentially refers to a feeling of exhaustion from using DLTs. While effectively used DLTs have been shown to enhance student learning and performance (Pimmer et al., 2019; So, 2016), excessive reliance on these platforms can lead to negative consequences (Cao and Sun, 2018). There have been studies on technological stress in occupational and commercial settings (e.g., workers and workplaces) which reported that technology frequently causes interruptions that lower productivity among employees and discourage technology use. Gadgets ostensibly intended to reduce the strain on human cognition can counter-productively render that load heavier (Grandhi et al., 2005; Karr-Wisniewski and Lu, 2010). These elements in particular show feelings of technology overload. However, few have examined the impact technology might have on students. Academic librarians in Pakistan reported a negative relationship between three essentials of technostress (i.e., uncertainty, invasion, and overload) and job satisfaction (Khan et al., 2013).

A growing body of research indicates that excessive technology use can lead to negative consequences, including stress, fatigue, decreased productivity, and job dissatisfaction, impacting knowledge workers, students, and instructors (Delpechitre et al., 2019; Khan et al., 2013; Mano and Mesch, 2010; Tarafdar et al., 2010). Studies have specifically linked technostress to poorer academic performance among students who spend too much time on devices (Yu et al., 2019). Additionally, research suggests that technology-induced stress (e.g., associated with SNSs and WhatsApp) can contribute to exhaustion and negatively impact perceived academic performance among university students (Al Abdullateef et al., 2021; Alvarez-Risco et al., 2021). While the majority of SNS fatigue research focuses on SNS and mobile instant messaging apps (Al Abdullateef et al., 2021; Lee et al., 2016a; Liu and Kuo, 2016; Shi et al., 2020; Yu et al., 2019; Zhang et al., 2016), other studies suggested that the beginning of screen fatigue in a proofreading experiment resulted in poorer user satisfaction (Park et al., 2019). Digital fatigue can increase energy expenditure when engaging with DLTs, potentially diverting time from essential learning tasks crucial to academic success. Students who rely heavily on DLTs may face challenges in effectively meeting learning demands because of the inherent difficulty of balancing technology use with dedicated study time. Consequently, we formulated the following hypothesis:

H7: *Students' perception of digital fatigue will be negatively related to students' performance when using DLTs.*

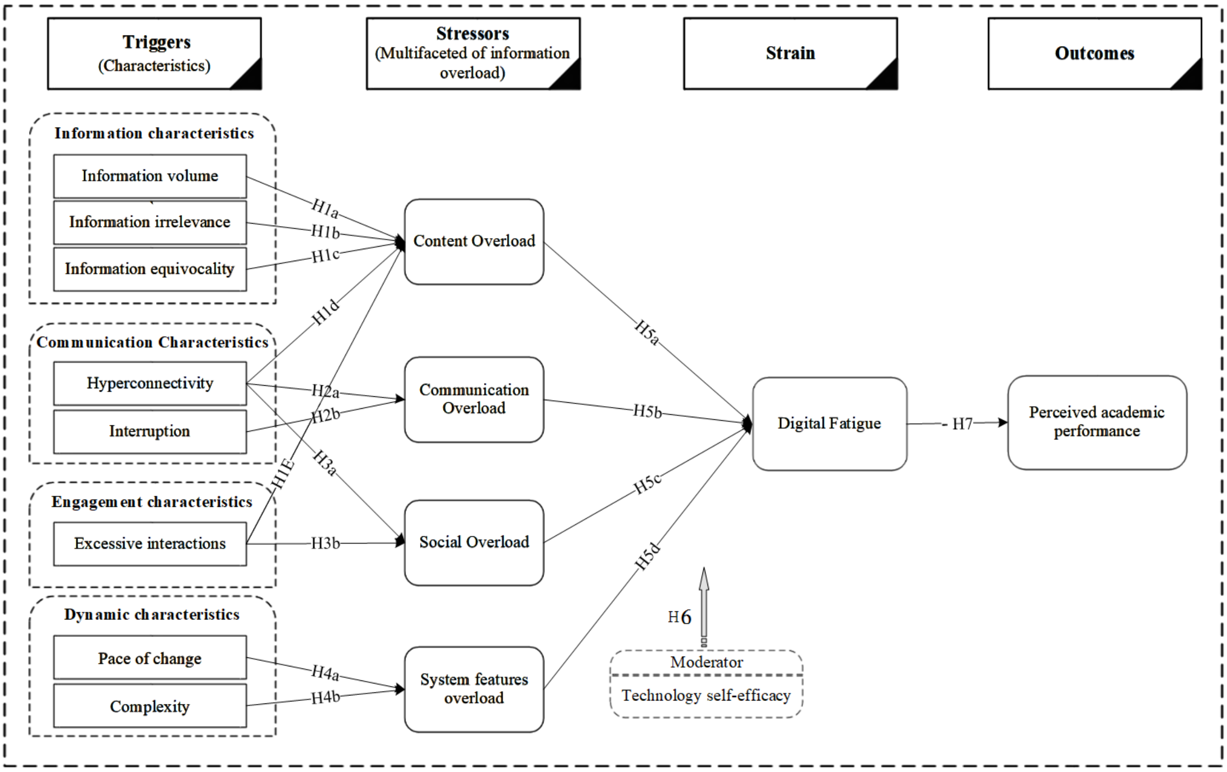


Figure 4.5: A Proposed Conceptual Framework for Information Overload in Digital Learning Tools

Chapter 5

Empirical Framework Testing Findings: Questionnaire Analysis

5.1 Introduction

The research findings are presented in this chapter. In alignment with the research objectives outlined in Chapter 1, this section analyses the data collected for the research. The findings provide insights into the demographic characteristics of the study's participants and the intricate relationships between the variables examined. By synthesising quantitative data, this chapter aims to shed light on the factors influencing the research outcomes, particularly focusing on the relationships identified through partial least squares structural equation modelling (PLS-SEM). The chapter also explores the demographic distribution of participants, offering an overview of the sample characteristics. The analysis delves into the reliability and validity of the measurement model, ensuring robust and credible results. Furthermore, the chapter examines the structural model to understand the complex interrelationships among variables. The data analysis was performed using PLS-SEM, using R for statistics and a version of the SEMinR package 2023.12.0 for measurement and structural equation modelling. The rest of the chapter is organised as follows: Section 5.2 discusses descriptive statistics, Section 5.3 covers the measurement model, Section 5.4 examines the structural equation model, and

Section 5.6 provides a summary of the chapter.

5.2 Descriptive Statistics

This section provides an overview of the data gathered from the research survey. Descriptive statistics form the foundation for summarising the key features of the data, offering insights into distributions and demographic data. The remainder of the section includes an outline of the dataset along with summary statistics and visual representations to give an understanding of the data.

5.2.1 Analysis of Distribution Frequency

The frequency analysis of student characteristics (N=200), which provides valuable insights into the demographic components of the studied population, is detailed here. As shown in Table 5.1, the gender distribution reveals that 41% of respondents were male (N=82), while 56.5% were female (N=113); 'other' was selected by 2.5% (N=5). Regarding age distribution, the majority of participants were between 22 and 35 years old, making up 59% (N=118) of the sample. Those aged 21 years or younger represented 20% (N= 40), while participants over 35 years old comprised 21% (N=42).

Participants were also categorised based on their field of study and their academic year. The most represented field was Humanities and Social Science, with 41% (N= 82) of participants pursuing studies in this area. This was followed by Science, which accounted for 34% (N= 68). Business and Engineering were less common, with 15.5% (N=31) and 9.5% (N=19) of participants, respectively. In terms of academic year, the distribution was relatively even across different years of study. Almost a third (31%, N= 61) were in their fourth year, making it the most represented academic year. The third year was close behind with 30% (N= 60). The second year accounted for 17% (N=34), and the first year represented 15.5% (N=31). Additionally, 18% (N=37) were categorised as being in 'other' academic years.

Table 5.1: Demographic Data Summary

Category		Frequency	Percent
Gender			
	Male	82	41
	Female	113	56.5
	Other	5	2.5
Age			
	$\leq$21-18	40	20
	22-35	118	59
	> 35	42	21
Field of studies			
	Science	68	34
	Engineering	19	9.5
	Humanities and Social Science	82	41
	Business	31	15.5
Academic year			
	1st year	31	15.5
	2nd year	34	17
	3rd year	60	30
	4th year	61	31
	Other	37	18

5.3 Measurement Model

The measurement model outlines the process for evaluating the quality of reflective measurement models within the PLS-SEM framework. This assessment encompasses both reliability and validity. Reliability is examined through composite reliability and both the item (indicator reliability) and construct levels (internal consistency reliability), while validity is assessed through convergent and discriminant validity. Convergent validity is determined by examining the average variance extracted (AVE), and discriminant validity is evaluated using the Fornell-Larcker criterion (Hair and Alamer, 2022).

5.3.1 Indicator Reliability

The initial step in evaluating a measurement model in PLS−SEM is to assess the reliability of each indicator by determining the proportion of its variance explained by the underlying construct. This is done by squaring the indicator's loading, which represents the correlation between the indicator and the construct. This indicator loading serves as a key measure for assessing the reliability and validity of the measurement mode (Hair et al., 2021). Any indicator with a statistically significant loading exceeding 0.708 is retained, thereby ensuring acceptable reliability. Thus, in Table 5.2, all items strongly correlate with their corresponding constructs, as indicated by the indicator loadings, surpassing the established threshold value. However, certain items with very low loadings (below 0.40), such as (IE2, IN2, and SO1) were excluded from the analysis, as their retention led to a decrease in both convergent validity and the internal consistency reliability (Hair and Alamer, 2022).

The items presented in Table 5.2, titled Factor Loadings, Means, and Standard Deviations for Constructs, represent the observed indicators used to measure the latent constructs within the research model. Each abbreviation corresponds to a specific construct as follows: Information Volume (IV), Information Irrelevance (II), Information Equivocality (IE), Hyperconnectivity (HY), Interruption (IN), Excessive Interaction (EI), Pace of Change (PC), Complexity (CX), Content Overload (CO), Communication Overload (CMO), Social Overload (SO), System Features Overload (SFO), Digital Fatigue (DF), Perceived Academic Performance (AP), and Technology Self-Efficacy (TSE). These indicators were adapted from validated scales in prior studies and operationalised to reflect the context of digital learning tools, which were discussed in Chapter 3. Their inclusion in the measurement model ensures that each construct is empirically represented by multiple indicators, thereby reinforcing the reliability and validity of the structural equation modelling analysis.

Table 5.2: Factor Loadings, Means, and Standard Deviations for Constructs

Construct	Item	Loading	Mean	Std. Deviation
Information volume				
	IV1	0.870	0.871	0.022

Construct	Item	Loading	Mean	Std. Deviation
	IV2	0.736	0.732	0.048
	IV3	0.885	0.885	0.019
Information irrelevance				
	II1	0.795	0.771	0.061
	II2	0.874	0.870	0.021
	II3	0.885	0.854	0.021
Information equivocality				
	IE1	0.957	0.952	0.022
	IE3	0.575	0.542	0.116
Hyperconnectivity				
	HY1	0.862	0.860	0.030
	HY2	0.856	0.844	0.033
	HY3	0.685	0.672	0.072
Interruption				
	IN1	0.699	0.688	0.080
	IN3	0.964	0.961	0.016
Excessive interactions				
	EI1	0.940	0.940	0.013
	EI3	0.944	0.942	0.013
Pace of change				
	PC1	0.773	0.706	0.233
	PC2	0.795	0.721	0.231

Construct	Item	Loading	Mean	Std. Deviation
	PC3	0.896	0.811	0.246
Complexity				
	CX1	0.784	0.781	0.037
	CX2	0.824	0.821	0.042
	CX3	0.850	0.849	0.026
Content overload				
	CO1	0.872	0.849	0.019
	CO2	0.684	0.669	0.060
	CO3	0.877	0.878	0.018
Communication Overload				
	CMO1	0.872	0.870	0.021
	CMO2	0.875	0.873	0.018
	CMO3	0.892	0.891	0.019
Social overload				
	SO2	0.685	0.675	0.099
	SO3	0.840	0.842	0.048
System feature overload				
	SFO1	0.845	0.844	0.026
	SFO2	0.920	0.919	0.013
	SFO3	0.906	0.904	0.015
Digital fatigue				

Construct	Item	Loading	Mean	Std. Deviation
	DF1	0.903	0.899	0.018
	DF2	0.744	0.744	0.055
	DF3	0.852	0.848	0.024
Academic Performance				
	AP1	0.831	0.825	0.034
	AP2	0.842	0.841	0.023
	AP3	0.795	0.789	0.044
	AP4	0.758	0.753	0.058
Technology self-efficacy				
	TSE1	0.891	0.888	0.030
	TSE2	0.817	0.813	0.051
	TSE3	0.775	0.766	0.068

Note. Factor loadings above 0.708 indicate strong indicator reliability. Items below 0.40 were removed. Means and standard deviations provide descriptive context for each indicator.

5.3.2 Internal Consistency, Reliability, and Convergent Validity

Table 5.3 provides a detailed evaluation of the internal consistency, reliability and convergent validity of multiple constructs within the measurement model. The constructs in the study generally exhibit strong internal consistency, as evidenced by the values of Cronbach's alpha coefficient and composite reliability values (rho_C and rho_A). Cronbach's alpha values range from 0.709 to 0.873, well above the threshold value of 0.70, indicating that the items within each construct consistently measure the intended concept. Similarly, the result for composite reliability (rho_C and rho_A) further supports the internal consistency of these constructs exceeding the 0.7 thresholds (Hair and Alamer, 2022), indicating that all construct measures are reliable. The convergent validity of the constructs is assessed using the average variance extracted (AVE), which measures how well a construct explains the variance in its indicators. All constructs in the study demonstrate good convergent validity, with AVE values consistently above the 0.50 threshold, ranging from 0.587 to 0.887. Constructs such as excessive interaction (AVE=0.887) and content overload (AVE=0.82) have particularly high AVE values, and are well exceeding the required minimum level of 0.50 (Hair and Alamer, 2022). Therefore, the measures of the constructs exhibit high levels of convergent validity. The constructs in the study demonstrate both well internal consistency reliability and convergent validity.

Table 5.3: Internal Consistency Reliability and Convergent Validity

Construct	**Cronbach's alpha**	**Composite reliability (rhoC)**	**Composite reliability (rhoA)**	**Average variance extracted (AVE)**
Information Volume	0.777	0.871	0.802	0.694
Information irrelevance	0.786	0.873	0.810	0.697
Information equivocality	0.734	0.750	0.841	0.616
Hyperconnectivity	0.727	0.841	0.782	0.640
Excessive interaction	0.873	0.940	0.873	0.887
Interruption	0.709	0.825	1.000	0.708
Pace of change	0.786	0.862	0.959	0.677
Complexity	0.755	0.859	0.758	0.671
Content overload	0.739	0.850	0.786	0.820
Communication overload	0.853	0.911	0.855	0.773
Social overload	0.724	0.738	0.722	0.587
System feature overload	0.868	0.920	0.874	0.792
Digital fatigue	0.776	0.871	0.799	0.693
Academic performance	0.823	0.880	0.860	0.647
Technology self-efficacy	0.776	0.826	0.840	0.687

Note: Cronbach's alpha and composite reliability values above 0.70 indicate internal consistency. AVE values above 0.50 confirm convergent validity.

5.3.3 Discriminant Validity

Another key aspect of validity assessment involves establishing discriminant validity, which ensures that each construct is empirically distinct and captures a unique phenomenon not represented by other constructs in the statistical model. The *Fornell and Larcker (1981)* criterion has commonly been the main standard for assessing discriminant validity (Hair and Alamer, 2022). In other words, discriminant validity, essential for validating the measurement model, is that the square root of each construct's AVE should exceed the highest correlation it has with any other construct in the model (Hair and Alamer, 2022).

Table 5.4 presents the results of the Fornell-Larcker criterion assessment, with the square root of each construct's AVE displayed on the diagonal and the correlations between constructs listed in the off-diagonal positions. For instance, the square roots of the AVEs for the constructs such as information volume (IV) (0.83), excessive interaction (IN) (0.94), and academic performance (AP) (0.80), all exceed the correlations between these constructs and other latent variables in the research framework. Summarising the findings, the measurement model distinguished between latent variables as most constructs showed satisfactory discriminant validity.

Given that all survey data were collected from the same respondents, the potential for common method bias (CMB) was evaluated using Harman's one-factor test (Podsakoff et al., 2003). CMB, which can inflate or deflate estimates and potentially lead to misleading conclusions (Kock, 2015). This test examines whether a single factor explains a majority of the variance, with a threshold of 50% indicating substantial CMB (Harman, 1976). The analysis yielded a single factor accounting for 33.292% of the variance, suggesting that no single factor dominated the data. Consequently, CMB is unlikely to be a significant threat to the study's conclusions.

Table 5.4: Discriminant Validity- Fornell Larcker

	IV	II	IE	HY	EI	IN	PC	CX	CO	CMO	SO	SFO	DF	AP	TSE
IV	**0.83**														
II	0.52	**0.83**													
IE	0.44	0.70	**0.78**												
HY	-0.33	-0.37	-0.29	**0.80**											
EI	0.65	0.50	0.42	-0.28	**0.94**										
IN	0.51	0.48	0.40	-0.25	0.62	**0.84**									
PC	0.14	0.20	0.22	0.13	0.27	0.26	**0.82**								
CX	0.58	0.55	0.44	-0.45	0.68	0.53	0.21	**0.82**							
CO	0.71	0.57	0.48	-0.41	0.67	0.55	0.13	0.70	**0.81**						
CMO	0.60	0.54	0.47	-0.35	0.68	0.58	0.19	0.67	0.72	**0.88**					
SO	0.55	0.40	0.39	-0.29	0.55	0.60	0.12	0.52	0.56	0.64	**0.77**				
SFO	0.64	0.55	0.51	-0.44	0.57	0.57	0.14	0.60	0.72	0.67	0.58	**0.89**			
DF	0.58	0.56	0.44	-0.48	0.63	0.56	0.12	0.66	0.71	0.60	0.58	0.66	**0.83**		
AP	-0.47	-0.42	-0.35	0.28	-0.43	-0.27	0.01	-0.49	-0.52	-0.41	-0.39	-0.45	-0.47	**0.80**	
TSE	-0.14	0.162	0.45	-0.29	-0.19	0.06	-0.41	-0.23	-0.22	-0.26	-0.21	-0.32	0.26	0.12	**0.83**

Note: The square root of AVE (diagonal) should exceed inter-construct correlations (off-diagonal) to confirm discriminant validity. Content overload (CO); Communication overload (CMO); Social overload (SO); System features overload (SFO); Information volume (IV); Information irrelevance (II); Information equivocality (IE); Hyperconnectivity (HY); Excessive interaction (EI); Interruption (IN); Pace of change (PC); Complexity (CX); Digital fatigue (DF); Perceived academic performance (PAP); Technology self-efficacy (TSE).

5.4 Structural Model Assessment

This section employs the structural model assessment as a powerful analytical tool to explore the intricate interrelationships among variables within the research framework. The assessment of the structural model in PLS-SEM begins with evaluating potential collinearity among predictor constructs in the structural model regressions. This is followed by examining the significance and relevance of the path coefficients, concluding with an analysis of the model's explanatory and predictive power. After confirming that model estimates are not adversely affected by high levels of collinearity through VIF value examination, we then test the significance of the path coefficients using a bootstrapping routine and evaluate bootstrap confidence intervals. To determine a model's explanatory power, the coefficient of determination (R^2) is used (Hair et al., 2021).

5.4.1 Assessment of Collinearity Issues

Structural model coefficients are derived from a set of regression equations. Nevertheless, the presence of strong interrelationships between predictor variables can distort these coefficients and their associated error estimates. Subsequently, it is crucial to examine the structural model regressions for potential collinearity issues to ensure accurate results (Hair and Alamer, 2022). To assess collinearity within each structural model regression, the construct scores of the predictor constructs are employed to compute the variance inflation factor (VIF) values. The results an assessment of collinearity issues through the examination of VIF scores. The VIF values ranged from 1.04 to 2.60, which are comfortably below the commonly accepted threshold of 3 (Becker et al., 2015; Hair and Alamer, 2022). This indicates that multicollinearity was not an issue in this model, ensuring that the relationships between the constructs were not distorted by high correlations among the predictor variables.

5.4.2 Interpreting Structural Model Results

Before presenting the path coefficients, it is helpful to clarify how to read the PLS–SEM outputs reported in this chapter. Path coefficients (β) denote the strength and direction of relationships between latent constructs; a positive β indicates a positive association and a negative β an inverse association. Statistical significance was assessed using nonparametric bootstrapping with 10,000 subsamples; t-values greater than 1.96 (two-tailed) and $p < .05$ indicate significance at the 95% confidence level. Bias-corrected 95% confidence intervals (CI) are reported to provide interval estimates that complement the t-tests.

The coefficient of determination (R^2) expresses the model's explanatory power for each endogenous construct. Following common benchmarks in the PLS–SEM literature (Hair et al., 2021), $R^2 \approx 0.25$ is considered weak, ≈ 0.50 moderate, and ≥ 0.75 substantial. These reference values aid the interpretation of the practical (predictive) significance of the relationships reported below.

5.4.3 Assessment of Path Coefficients

PLS-SEM utilises regression analysis and path analysis through a scientific approach to enhance researchers' comprehension of the complex relationships between variables. In this study, the full bootstrapping method was employed for this research framework, with 10,000 subsamples, as recommended, to test the path coefficients (Hair et al., 2021). The assessment of path coefficients presented in Table 5.5 and Figure 5.1 offer broad insights into the correlations within the research framework. These correlations include DLTs characteristics (information volume, information irrelevance, information equivocality, hyperconnectivity, excessive interaction, interruptions, pace of change, and complexity) as triggers, also the framework examines dimensions of IO (content, communication, social, and system features) as a mediator, and its impact on digital fatigue, ultimately influencing the academic performance of students. Information volume and information irrelevance expose a positive and statistically significant relationship with content overload (t= 6.11, β= 0.38, CI 95% [.0.25, 0.50]), t= 2.10, β= 0.13, CI 95% [.0.00, 0.27], respectively), thus affirming hypotheses H1a and H1b.

Similarly, excessive interaction significantly influences two dimensions of IO that positively impact content overload and social overload (t= 4.12, β= 0.29, CI 95% [.0.15, 0.43], t= 8.487, β= 0.51, CI 95% [.0.39, 0.62], respectively), resulting in the acceptance of hypotheses H1e and H3b. However, information equivocality has a positive but insignificant relationship with content overload (t=0.98 β= 0.05, CI 95% [-0.06, 0.17]), resulting in the rejection of hypothesis H1c. Moreover, hyperconnectivity has a statistically significant but negative relationship with content overload (t= -2.92 β= -1.14, CI 95% [-0.23, 0.05]), resulting in the rejection of hypotheses Hd1, because the relationship is negative, not positive. Likewise, hyperconnectivity is negative and strongly influences on communication overload (t = -3.19 β= -0.21, CI 95% [-0.35, 0.08]), leading to the rejection of hypotheses H2a. Interruption demonstrated a significant positive relationship with communication overload (t = 11.20, β= .52, CI 95% [.0.43, 0.61]), supporting H2b. Complexity revealed a significant positive correlation with system features overload, supporting H4b (t=11.98 β = 0.59, CI 95% [0.49, 0.68]). In contrast, the pace of change exposed an insignificant positive correlation with system features overload (t = 0.16 β = 0.01, CI 95% [0.13, 0.15]), leading to the rejection of hypotheses H4a. Several dimensions of IO (content, social, and system features overload) significantly influence and positively impact digital fatigue dimensions (t =5.20 β = 0.42, CI 95% [0.26, 0.58]), (t =3.04 β = 0.20, CI 95% [0.07, 0.32]), (t=3.07 β = 0.24, CI 95% [0.89, 0.39]), respectively), supporting hypotheses H5a, H5c, and H5d. This highlights the critical impact of various dimensions of IO in exacerbating digital fatigue. However, the relationship with the communication overload manifestation in hypothesis H5b is rejected because of a statistically insignificant relationship with digital fatigue. This indicates that, unlike other dimensions of IO, communication overload does not have a significant impact on digital fatigue in the context of DLTs. Digital fatigue was found to be negatively and significantly associated with perceived performance (t = -7.34, β = -0.46, CI 95% [-0.59, -0.34]), thereby confirming hypothesis H7. This underscores the detrimental impact of digital fatigue on students' perceived academic performance.

Table 5.5: Structural Model Results Showing Path Coefficients, Mean, Standard Deviation, T-Values, 95% Confidence Intervals, and Hypothesis Decisions

Path	β	**Mean**	**STDEV**	**T Values**	**92.5% CI**	**97.5% CI**	**Hypothesis**	**Decision**
IV → CO	0.382	0.381	0.062	6.115	0.258	0.501	H1a	accepted
II → CO	0.138	0.139	0.071	2.001	0.006	0.275	H1b	accepted
IE → CO	0.059	0.060	0.060	0.981	-0.061	0.176	H1c	rejected
HY → CO	-0.141	-0.143	0.048	-2.925	-0.236	-0.050	H1d	rejected
HY → CMO	-0.217	-0.221	0.068	-3.192	-0.350	-0.083	H2a	rejected
HY → SO	-0.151	-0.152	0.084	-1.785	-0.310	0.016	H3a	rejected
EI → CO	0.290	0.291	0.070	4.127	0.154	0.430	H1e	accepted
EI → SO	0.510	0.513	0.060	8.487	0.391	0.625	H3b	accepted
IN → CMO	0.526	0.528	0.047	11.200	0.431	0.614	H2b	accepted
PC → SFO	0.011	0.026	0.068	0.161	-0.133	0.152	H4a	rejected
CX → SFO	0.594	0.593	0.050	11.987	0.490	0.685	H4b	accepted
CO → DF	0.422	0.425	0.081	5.205	0.262	0.581	H5a	accepted
CMO → DF	0.004	0.004	0.085	0.052	-0.165	0.172	H5b	rejectd
SO → DF	0.200	0.202	0.066	3.041	0.071	0.328	H5c	accepted
SFO →DF	0.243	0.242	0.079	3.075	0.089	0.397	H5d	accepted
DF → AP	-0.468	-0.475	0.064	-7.345	-0.592	-0.345	H7	accepted

Note: Content overload (CO); Communication overload (CMO); Social overload (SO); System features overload (SFO); Information volume (IV); Information irrelevance (II); Information equivocality (IE); Hyperconnectivity (HY); Excessive interaction (EI); Interruption (IN); Pace of change (PC); Complexity (CX); Digital fatigue (DF); Perceived academic performance (PAP); Technology self-efficacy (TSE).

5.4.4 The Model's Explanatory Power

The next step is to assess the coefficient of determination (R^2) and its adjusted form for the endogenous constructs, as shown in Table 5.6. R^2 represents the proportion of variance explained in each endogenous construct and serves as an indicator of the model's explanatory power (Hair et al., 2021). For the IO dimensions (content, communication, system features, and social overload), the R^2 values indicate that the model explains approximately 63%, 38%, 36%, and 33% of the variance, respectively, suggesting substantial explanatory strength. Similarly, the model accounts for about 58% of the variance in digital fatigue, while perceived academic performance shows an R^2 of 22%, which aligns with prior findings (Al Abdullateef et al., 2021).

Adjusted R-squared R^2 is a refined version of R^2 that accounts for the number of predictors in the model. Unlike the standard R^2, which always increases when new variables are added (even if irrelevant), adjusted R^2 penalises unnecessary variables, providing a more accurate measure of explanatory power (Hair et al., 2021). In this research, the adjusted values remain nearly consistent with the regular R^2, confirming that the model's explanatory strength is not artificially inflated by model complexity. Overall, these coefficients demonstrate the model's robustness in explaining variance across overload dimensions, digital fatigue, and academic performance.

Table 5.6: Coefficient of determination

	R^2	R^2 **Adjusted**
Content overload	0.632	0.622
Communication overload	0.380	0.374
Social overload	0.325	0.318
System features overload	0.356	0.349
Digital fatigue	0.581	0.572
Perceived academic performance	0.219	0.214

Note: R^2 indicates the proportion of variance explained by the model for each construct. Adjusted R^2 corrects for the number of predictors, ensuring that explanatory power is not inflated by adding irrelevant variables.

Figure 5.1 below is derived directly from the empirical estimates reported in Table 5.5 and 5.6. It provides a graphical representation of the structural model, where each path corresponds to the standardised coefficient (β) presented in the table. Solid lines denote positive relationships, with bold solid lines indicating statistically significant positive paths at $p < .05$, based on bootstrapping with 10,000 subsamples. Dotted lines represent negative relationships. Numerical values on the paths indicate the standardised coefficients (β), while values in parentheses within the endogenous constructs represent the coefficient of determination (R^2), reflecting the proportion of variance explained by the model. This visualisation facilitates an integrated interpretation of the model's predictive capability and highlights the most influential relationships, such as the strong positive effect of interruption on communication overload ($\beta = 0.526$) and the significant negative association between digital fatigue and perceived academic performance ($\beta = -0.468$).

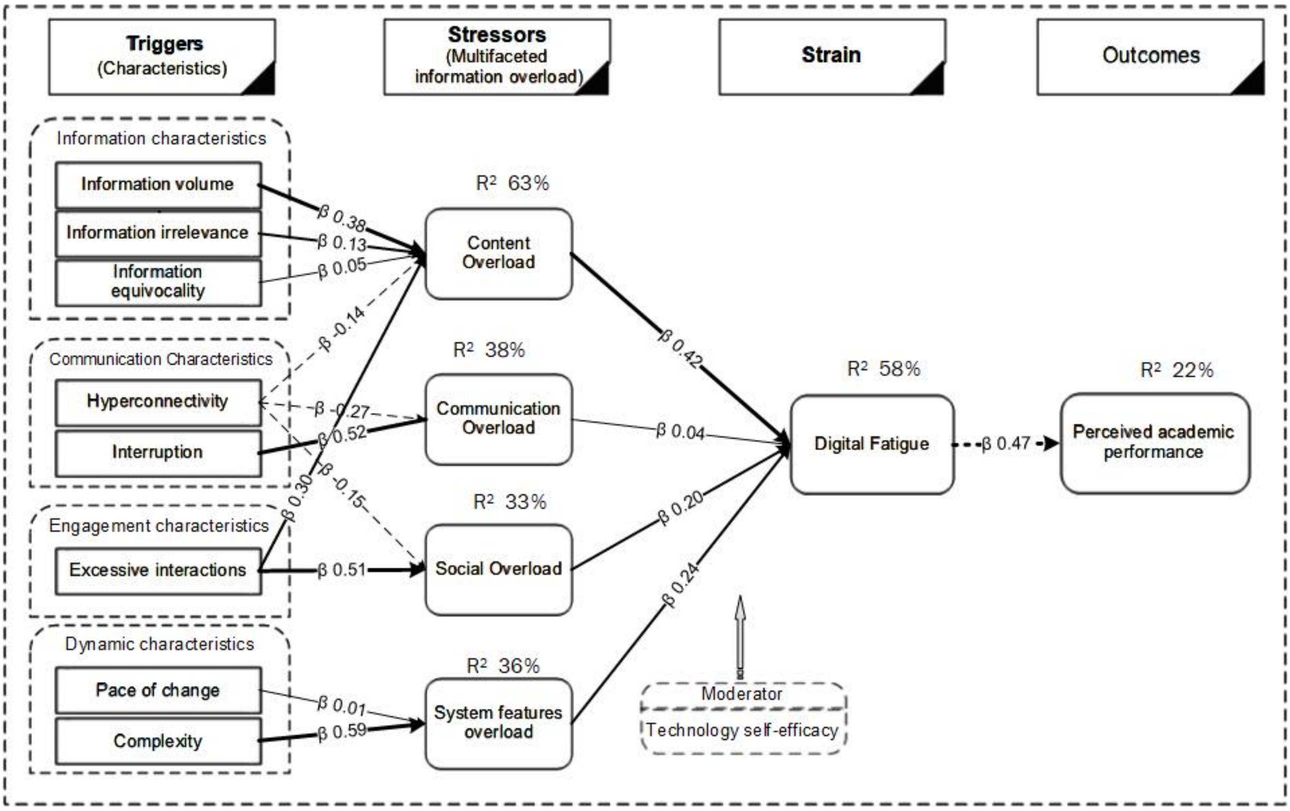


Figure 5.1: PLS-SEM bootstrapping model with path coefficients and explained variance

Note: Solid lines represent positive paths; bold solid lines indicate statistically significant positive paths; dotted lines represent negative. Numbers on the paths are standardised coefficients (β), and values in parentheses (R^2) indicate explained variance.

5.5 Moderating Effects

The impact of a moderating variable on the connection between independent and dependent variables demonstrates that this relationship is not consistent; rather, it hinges on the values of a third variable known as the moderator (Hair and Alamer, 2022). In this research, technology self-efficacy serves as a moderating variable, and the moderation effect is tested using the bootstrapping method. The moderation analysis results reveal that students' technology self-efficacy plays a significant role in moderating the relationship between content overload and digital fatigue. As can be seen in Table 5.7, the interaction term (content overload * technology-self efficiency) has a positive effect on digital fatigue of 0.183, whereas the simple effect of content overload on digital fatigue is 0.422. Jointly, these results suggest that the relationship between content overload on digital fatigue is 0.422 for an average level of technology-self efficiency. For higher levels of technology-self efficiency (i.e., for every standard deviation unit increase of technology-self efficiency), the relationship between content overload and digital fatigue increases by the size of the interaction term (i.e., $0.422 + 0.183 = 0.605$). Conversely, for lower levels of technology-self efficiency (i.e., for every standard deviation unit decrease of technology-self efficiency), the relationship between content overload and digital fatigue decreases by the size of the interaction term (i.e., $0.422 - 0.183 = 0.235$). To better comprehend the results of the moderation analysis, Figure 5.2 presents a slope analysis (moderation plot) illustrating the interaction effect between content overload and technology self-efficacy on digital fatigue. The analysis reveals that students with higher technology self-efficacy experience a stronger positive relationship between content overload and digital fatigue, suggesting that as their confidence in handling technology increases, so does their susceptibility to fatigue when faced with content overload. At an average level of technology self-efficacy, content overload has a moderate impact on digital fatigue, reflecting a balanced relationship. Conversely, students with low technology self-efficacy perceive a weaker relationship between content overload and digital fatigue, indicating that they experience lower fatigue levels in response to content overload.

Conversely, the moderation effects of communication overload, social overload, and system feature overload on digital fatigue are negative but insignificant. Communication overload and technology self-efficacy interaction (t = -0.176, *beta* =-0.062, CI 95% [0.192, 0.158]) show no significant moderation, social overload and technology self-efficacy interaction (0.015, t = 0.212, *beta*=0.015, CI 95% [-0.151, 0.133]) also shows no significant moderation, and system feature overload and technology self-efficacy interaction (t = -0.801,*beta* = -0.057, CI 95% [-0.187, 0.085]) shows no significant moderation. These results indicate that students' technology self-efficacy does not significantly moderate the relationships between communication overload, social overload, and system feature overload with digital fatigue. A complete picture of PLS bootstrapping moderation is shown in Appendix E.

In summary, while technology self-efficacy strengthens the relationship between content overload and digital fatigue, it does not significantly influence the relationship involving other types of overload.

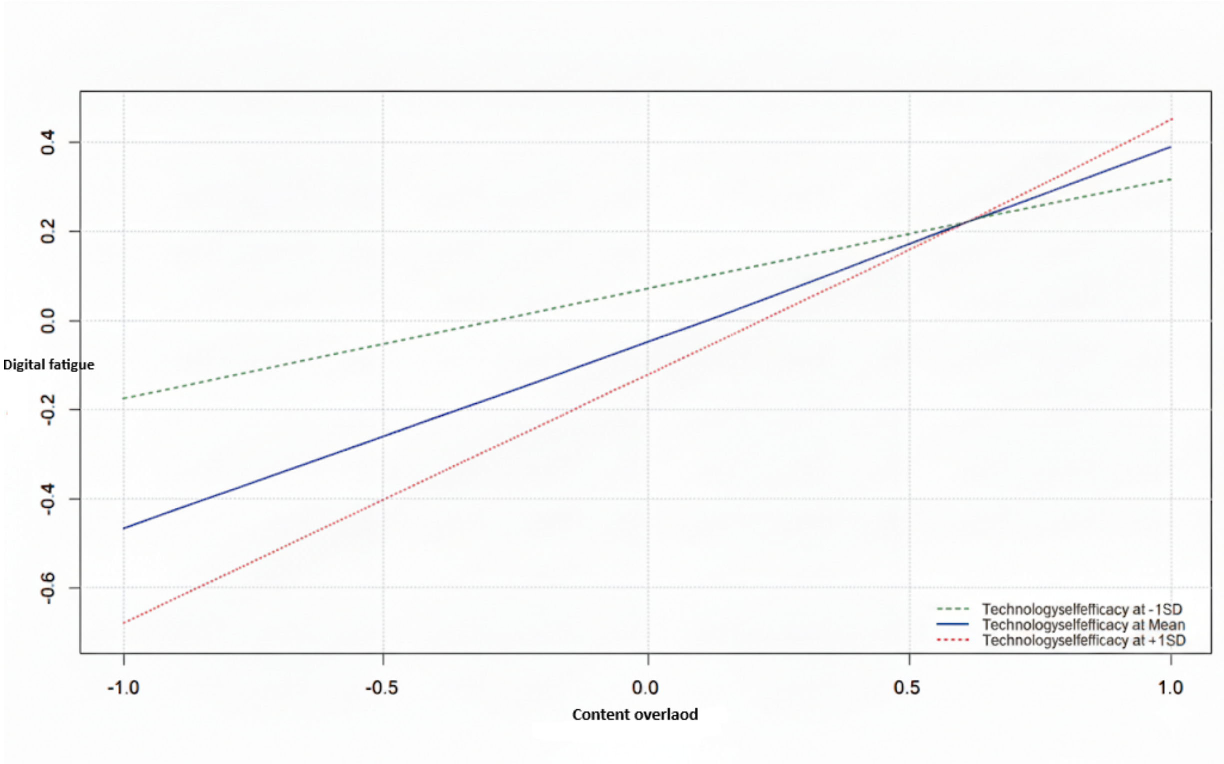


Figure 5.2: Graph illustrating the moderation effect of technology self-efficacy

Table 5.7: Results of moderating effects

Relationship	β	Bootstrap	T values	2.5% CI	97.5% CI	Decision
CO*TSE → DF	0.183	0.075	2.430	0.034	0.324	Significant
CMO*TSE → DF	-0.062	0.097	-0.640	-0.256	0.119	Not Significant
SO*TSE → DF	-0.015	0.070	0.212	-0.151	0.133	Not Significant
SFO*TSE → DF	-0.057	0.071	-0.801	-0.187	0.085	Not Significant

5.6 Chapter Summary

This chapter assessed relationships using PLS-SEM and moderation analysis. As shown in Table 5.5, 10 of 16 hypotheses were supported (e.g., H1a, H1b, H1e, H3b, H2b, H4b, H5a, H5c, H5d, H7), confirming strong effects of content, social, and system feature overload on digital fatigue, which negatively impacts perceived academic performance.

Six hypotheses (H1c, H1d, H2a, H3a, H4a, H5b) were rejected, revealing unexpected or weak relationships, such as the negative effect of hyperconnectivity and the non-significance of communication overload. These findings highlight gaps for future research and, together with supported hypotheses, reinforce the need for targeted interventions to manage IO.

Moderation analysis showed that technology self-efficacy significantly amplified the effect of content overload on digital fatigue, while other moderation effects were non-significant.

Chapter 6

Strategies for Dealing with Information Overload: A Systematic Review

6.1 Introduction

Given that the previous phase of this research provided empirical evidence indicating that IO is positively associated with strain (i.e., digital fatigue) and negatively associated with perceived academic performance, it is essential to recognise the countermeasures highlighted in previous studies through a systematic review. Consequently, the escalating issue of IO in the information age necessitates a broader examination of potential solutions. Although previous reviews have investigated the effects of IO and coping strategies, these studies have primarily been confined to specific fields such as medicine or work (Camarena et al., 2022; Nijor et al., 2022; Seidler et al., 2018; Waller et al., 2019), business (Arnold et al., 2023; Hartmann and Weibenberger, 2024; Roetzel, 2019; Thomas Craig et al., 2021). Research addressing this issue remains notably scarce across various disciplines, highlighting a significant scarcity in the literature that extends to a multidisciplinary study (Shahrzadi et al., 2024).

A systematic review is a structured approach to reviewing research that uses explicit methods to find and combine the results of studies answering a specific question (Chandler et al., 2019). While systematic reviews offer a rigorous and structured approach to synthesising research, they also have several limitations, particularly outside the medical domain. Conducting a systematic review can be time-consuming and resource-intensive, requiring careful planning and exhaustive literature searches. The rigid inclusion and exclusion criteria often used may overlook relevant studies that do not strictly fit predefined parameters. Additionally, systematic reviews can be affected by publication bias, as unpublished or grey literature is frequently excluded. In non-medical fields, such as information systems or social sciences, assessing the quality of studies is more challenging due to the diversity of research methods, and some contextual or qualitative insights may be underrepresented. Consequently, while systematic reviews provide valuable evidence synthesis, their applicability and flexibility can be limited in certain disciplinary contexts (Boell and Cecez-Kecmanovic, 2015; Okoli, 2015). This systematic review aims to categorise and analyse tools and interventions for managing IO based on their primary focus: reducing incoming information or improving information handling. Moreover, the research will combine insights from various disciplines to devise strategies to combat IO. The research question for this review was: *What strategies are used to manage or alleviate IO?*

6.2 Method

This research adheres to the "Preferred Reporting Items for Systematic Reviews" (PRISMA) 2020 statement, a set of guidelines for conducting and reporting systematic reviews. PRISMA 2020 is a guideline primarily for systematic reviews of health interventions. However, it can be adapted for reviews of other types of interventions (like social or educational), and even for reviews that do not evaluate interventions (e.g., those studying causes, frequency, or outcomes of health conditions) (Matthew et al., 2021).

6.2.1 Search Strategy

In May 2024, a cross-disciplinary search was conducted across four major academic databases: LISA (Library and Information Science Abstracts), PubMed, IEEE, and Taylor & Francis. LISA, specialising in library and information science, provides foundational knowledge relevant to this research. IEEE, with its emphasis on technological approaches such as algorithms, is essential for understanding the technological dimensions of the problem. PubMed, focusing on biomedical literature, delivers critical insights into the cognitive and psychological impacts of IO, particularly in healthcare. For example, studies highlight how the adoption of electronic health records has increased IO for physicians and nurses, emphasising the need to identify key patient-specific information to support better clinical decisions (Clarke et al., 2013). Finally, Taylor & Francis offers a broader perspective and interdisciplinary content across social sciences, humanities, and technology studies.

The subsequent step involved conducting a keyword search within the selected databases to identify relevant papers. The literature often employs varied and inconsistent terminology to describe the prevention and reduction of IO, including terms such as "solution," "coping mechanism," "countermeasure," and "intervention." For this review, the list of terms was directly drawn from a similar systematic review focused on prevention and intervention strategies for IO (Arnold et al., 2023). The systematic review aimed to clarify two primary concepts: information overload and the associated strategies (see Table 6.1 for details).

The search strategy utilised wildcards to adapt search strings for different database requirements. The search encompassed four databases, focusing specifically on peer-reviewed academic articles and complete conference papers. The screening process began with a systematic review of titles and abstracts to ensure topic relevance. This initial keyword search identified 861 papers across databases. Following deduplication, the collection was refined to 438 articles for further analysis.

Table 6.1: Search String

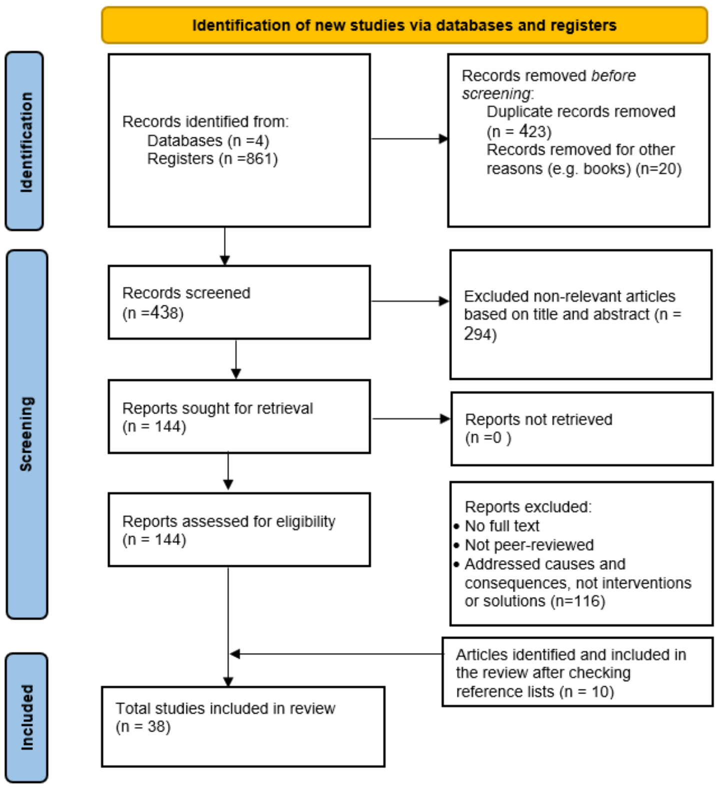
Concept	Terms
Overload	("*information overload" OR "overload of information" OR "information load") AND
Intervention	("*preventing" OR "*intervention" OR "reducing" OR "*countermeasure" OR "remedy" OR "overcoming" OR "*filtering" OR "dealing with" OR "*coping with" OR "*strategies" OR combat OR management OR control OR prevent* OR reduction)

Inclusion and Exclusion Criteria

The following criteria were established to assess the eligibility of studies for inclusion in the review, ensuring that only relevant and high-quality research was considered. Studies were included if they: (1) specifically examined interventions and prevention strategies for IO; (2) presented original research in peer-reviewed, full-text articles; (3) described preventative measures, remedial solutions, and adaptive techniques for addressing IO; and (4) were written in English. Articles that solely discussed the causes and consequences of IO, without addressing interventions or solutions, were excluded from the review.

To ensure the relevance of studies to the research question, I applied inclusion and exclusion criteria across multiple stages. Initially, 438 records underwent screening based on titles and abstracts, leading to the exclusion of 294 non-relevant articles. Subsequently, 144 reports were sought and assessed for eligibility. At this stage, 116 reports were excluded due to reasons such as not being accessible in full-text versions, not being peer-reviewed, or not focusing on interventions or solutions. Finally, 10 additional articles were identified through manual reference list checking, bringing the total number of studies included in the review to 38. The PRISMA flow diagram of this process is shown in Figure 6.1

Figure 6.1: PRISMA flow diagram for the systematic review process



6.2.2 Data Extraction and Synthesis

Data were systematically extracted using a custom-designed extraction form, developed to ensure consistency and transparency across all included studies. This form served as a structured template for capturing essential details, including citation information (authors, year, and publication source), study context (country, setting), methodological approach (design and sample size), participant characteristics, and key findings. The extraction process was implemented using Microsoft Excel spreadsheets, which allowed for organised data entry, easy filtering, and efficient comparison across studies. The extracted data also included information regarding preventive approaches, remedial solutions, and coping mechanisms for managing information overload, enabling a deep synthesis of approaches reported in the literature. Using this form ensured that data collection was comprehensive, comparable across studies, and aligned with PRISMA guidelines, thereby supporting the reliability and reproducibility of the review.

6.2.3 The Characteristics of Included Studies

Methodological Overview

Considering the diversity of the included studies, the results were organised according to a general methodological framework, followed by specific techniques. This approach allowed for highlighting various methodological strategies, illustrating their interconnectedness and demonstrating how they collectively contribute to the topic. The articles were categorised into three methodologies: quantitative, qualitative, and mixed methods.
Articles were categorised by research methodology through a two-step process: first by identifying explicit methodological declarations (qualitative, quantitative, or mixed-method), and when such declarations were absent, by examining the described research designs and methods to determine the appropriate classification. Articles employing statistical tests, numerical data analysis, and algorithms (e.g., collaborative filtering and recommendation systems) were categorised as quantitative. Those involving interviews and focus groups were classified as qualitative, while methodologies that combined both quantitative and qualitative approaches were categorised as mixed methods. A total of 38 studies that met the inclusion criteria were included in the systematic review, the majority of which used quantitative methods (n = 20), followed by qualitative approaches (n = 16), and mixed-methods approaches (n = 2)

Characteristics of Included Studies

This section details the methodological distribution and geographical origins of the included studies. Among them, 20 were quantitative articles, 20 were quantitative articles (Ellwart et al., 2015; Gaudioso et al., 2017; Gayo-Avello et al., 2003; Gerosa et al., 2001; Graf and Antoni, 2021; Huang et al., 2024; Iatraki et al., 2018; Jia and Wang, 2021; Jian et al., 2022; Kang and Chung, 2022; Khalid et al., 2021; Lei et al., 2022; Lin et al., 2022; Lines and Denstadli, 2004; Porcel et al., 2010; Soucek and Moser, 2010; Turetken and Sharda, 2004; Tzagarakis et al., 2014; Wang, 2022), 16 were qualitative studies

(Blummer and M. Kenton, 2014; Cheng and Vassileva, 2006; Clarke et al., 2013; Johnson, 2014; Klerings et al., 2015; Koen et al., 2018; Landale, 2007; Lauri et al., 2021; Liu and Kuo, 2016; Mahdi et al., 2020; Savolainen, 2007; Saxena and Lamest, 2018; Shachaf et al., 2016; Stadin et al., 2020; Sweeny et al., 2010; Voinea et al., 2020), and two were mixed-methods study designs (Jones and Kelly, 2018; Lauri and Virkus, 2019). The published articles represent diverse geographical origins, with the greatest representation for the USA (n=10), followed by the UK (n=7), Germany (n=6), China (n=5), and Spain (n=3). 'Other countries' were covered by 7 studies, including Austria, Canada, Estonia, Finland, Greece, Ireland, Norway, South Africa, and Sweden, reflecting a diverse distribution across various research contexts (see figure 6.2). In terms of the distribution of

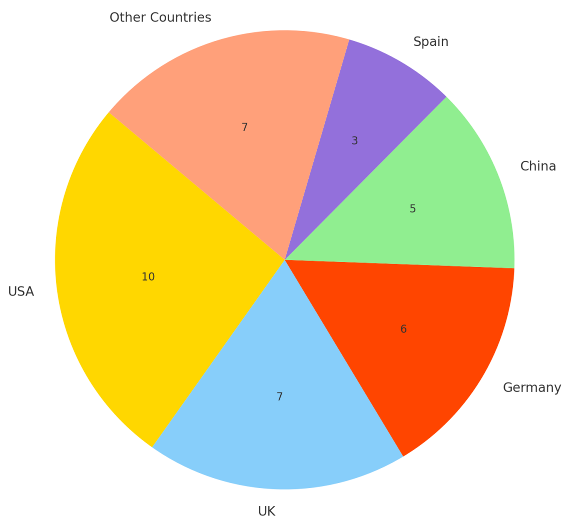


Figure 6.2: Country of origin of reviewed studies

studies included in the review by year of publication (see figure 6.3), the earliest study was published in 2000, with one study reported, and there were gaps in included studies for several years, including 2001–2003, 2005–2006, 2008, and 2011–2013. The highest number of studies was published between 2022 and 2023, with 4 studies in 2022 and 1 study in 2023, indicating an increase in awareness among researchers about the importance of handling information overload in more recent years. Moderate counts of two studies per year were observed in 2004, 2007, 2009, 2014, and 2017–2020. Overall, the chart reflects a scattered trend in publication over time, with a notable rise in studies in more recent years, particularly between 2022 and 2023.

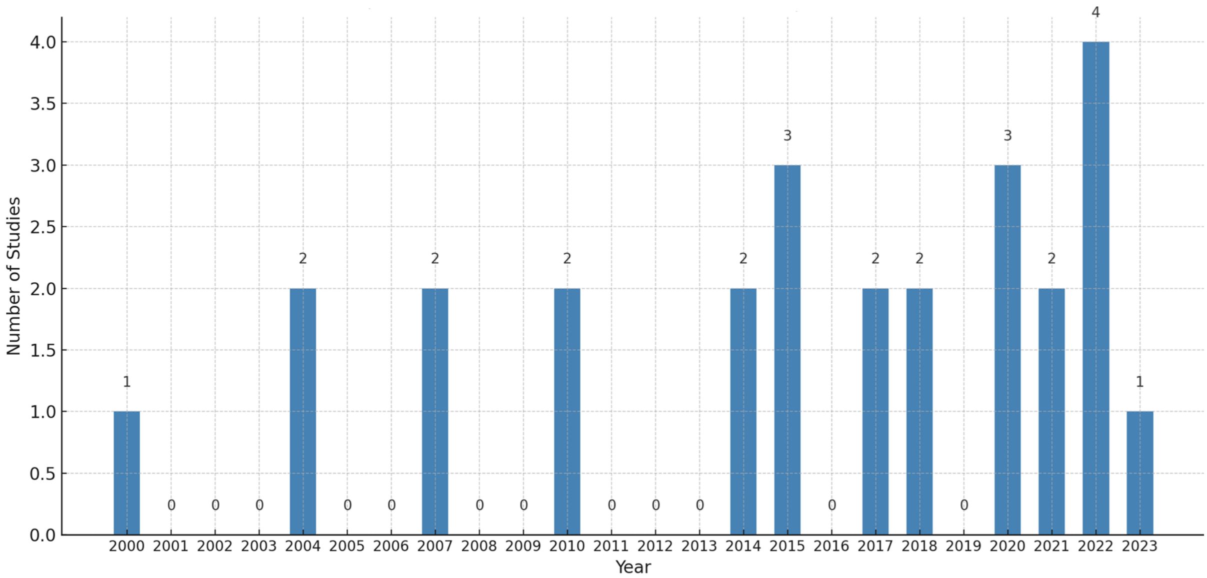


Figure 6.3: The number of papers by publication year

Upon examining the subject matter of reviewed articles, it is clear that the education sector was the most frequently explored field (n = 12), followed by the healthcare sector (n = 7). By incorporating a broad approach that spans various countries, methodologies, discipline areas, prevention methods, solutions, and coping strategies, these articles collectively enhance our understanding of the matter under investigation. The reviewed literature spans 31 unique publication venues, as shown in Table 6.2. This distribution across multiple journals and conferences demonstrates both the broad academic interest in IO and the multidisciplinary approaches being taken to address this challenge. Further details regarding the reviewed studies and the characteristics of these studies can be found in Appendix G.

Table 6.2: Publication Venues

Publication Type	Names	Frequency
	Journal of Documentation	3
	Computational Intelligence and Neuroscience	3
	Computers in Human Behavior	2
Academic Journal	European Journal of Work and Organisational Psychology	2
	Journal of Information Science	2
	Soft Computing	1
	PLOS ONE	1
	BMC Medical Informatics and Decision Making	1
	International Journal of Consumer Studies	1
	Evidence, Training and Quality in Health Care	1
	User Modelling and User-Adapted Interaction	1
	Sensors	1
	Science and Engineering Ethics	1
	Research Challenges in Information Science	1
	Library & Information Science Research	1
	International Journal of Medical Informatics	1
	IEEE Transactions on Neural Networks	1
	College & Undergraduate Libraries	1
	IEEE Access	1
	Human-Computer Interaction	1
	Entropy	1
	Educational Technology & Society	1
	Control and Cybernetics	1
	Ecancer Medical Science	1
	Frontiers in Artificial Intelligence and Applications	1
Conference Proceedings		

International Conference on Information Science and Education	1
Information Literacy in Everyday Life	1
IEEE Xplore	1
Information Technologies in Science, Management, Social Sphere and Medicine	1
Computer and Information Sciences	1

6.3 Data Analysis

Thematic analysis is used for identifying, analysing, and interpreting patterns or themes within a dataset. It enables researchers to systematically code, organise, and uncover meaningful themes in the data. Qualitative approaches are highly diverse, complex, and nuanced, and thematic analysis is often regarded as a foundational method for conducting qualitative analysis (Braun and Clarke, 2006). This research benefits from thematic analysis because it allows for a deeper exploration of generating and emerging themes, which is ideal for understanding and providing insight into existing prevention and intervention measures related to IO. Following the approach of Braun and Clarke (2006), which distinguishes between top-down (deductive) and bottom-up (inductive) approaches, this study adopted an inductive reasoning approach. This methodology allowed themes to emerge naturally from the data while addressing predetermined research questions. In practice, they note that most analyses tend to fall somewhere between these two orientations and perspectives, suggesting that they should be viewed as points on a continuum rather than as distinct binary positions. Similarly, I adopted inductive approaches when analysing strategies and interventions related to IO. The thematic analysis framework, outlined by the six stages of Braun and Clarke (2006), as unpacked in the next section, and adumbrated below:

- Familiarisation with the data.

- Generating initial codes.
- Searching for themes.
- Reviewing themes.
- Defining and naming themes.
- Producing the report.

6.3.1 Thematic Analysis

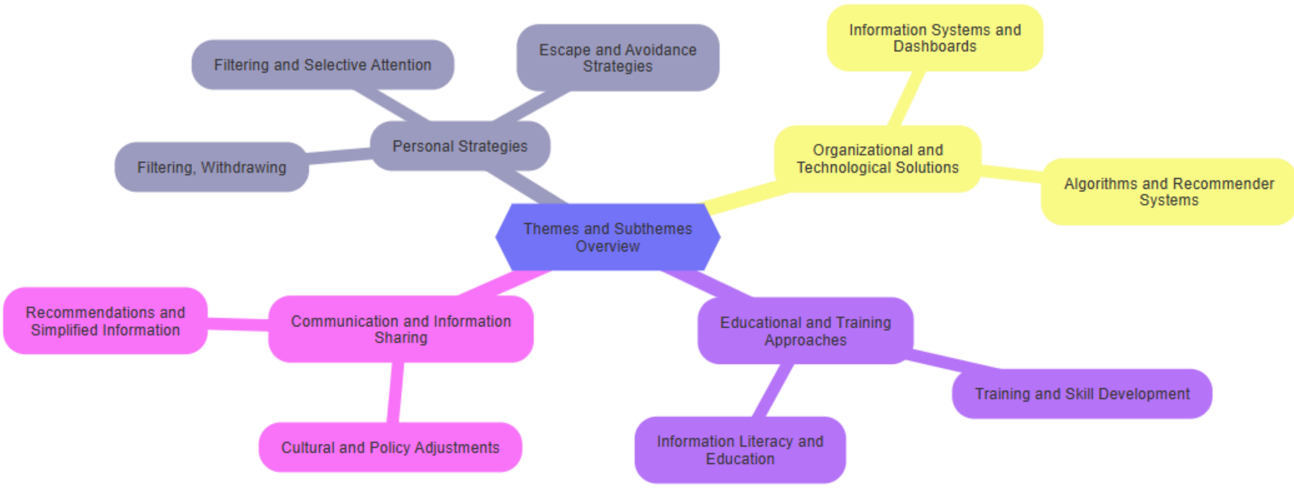
Thematic analysis was conducted across the 38 articles using the six-phase approach outlined by Braun and Clarke (2006), as follows:
1- Braun and Clarke (2006) describe this phase as one in which the researcher becomes "intimately familiar" with the data set through repeated reading. In this systematic review, the selected articles were printed as hard copies and read thoroughly. The process involved examining the relationships between the study's research question and the content of the articles. During this phase, it is beneficial to begin jotting down notes or highlighting ideas for potential coding, which can be revisited and refined in later stages (Braun and Clarke 2006). I noted points of interest and identified potential codes.
2- As described by Braun and Clarke (2006), thematic analysis involves systematically coding notable features of the data across the entire dataset and organising data relevant to each code. According to Braun and Clarke (2006, p. 87), "the process of coding is part of analysis." In this study, I interpreted textual data in relation to the research question to generate initial codes. For example, sentences such as "identifying and prioritising critical information while ignoring irrelevant content (e.g., filtering emails or documents based on urgency and relevance)," and "focusing on high-quality information sources and avoiding low-priority channels" were labeled with the code " personal strategies." In addition, I applied multiple codes to individual sentences or, occasionally, to groups of interconnected sentences to form clusters of codes that accurately represented the meaning of each text.

3-Braun and Clarke (2006) suggest that researchers take several factors into account when identifying themes, such as determining whether a central concept unifies the data, assessing how each theme relates to others, and ensuring there is sufficient data to support the theme. Following this approach, I generated initial themes by analysing the codes and identifying cross-comparative patterns across multiple articles. However, it was unclear whether these would form standalone themes, subthemes, or fail to develop into themes altogether. At this point, it was essential to pause, and " this is when you start thinking about the relationship between codes, between themes, and between different levels of themes" (Braun and Clarke, 2006, p. 89). I found that some initial codes developed into main themes, while others became sub-themes, and some were ultimately discarded.

4- Braun and Clarke (2006) define a theme as a cluster of categorised (or coded) data that "represents some level of patterned response or meaning within the dataset" (p. 82). However, they clarify that a theme is not solely determined by its prevalence across multiple data sources. Instead, they emphasise the importance of researcher's judgement in evaluating the significance of a theme. Braun and Clarke stress that the relevance of a theme should be assessed based on its connection to the research questions rather than its frequency within the dataset. The key research question in this study is, *What strategies are used to manage or alleviate IO?"* At this stage, it was essential to carefully evaluate whether the identified themes were not only relevant to the overarching research question but also reflective of the narrative within the data. For example, 'personal strategies' was identified as a standalone theme because the strategies discussed under this category in the studies consistently addressed how individuals actively coped with or managed information overload, directly responding to the research question about management strategies. The recurrence of these individual-level approaches across the dataset underscored their significance in the context of IO management, as revealed by the data's narrative.

5-Braun and Clarke (2006) recommends creating "theme definitions" to establish clear focus and boundaries for each theme (p. 249). During the initial coding process and while reviewing the articles, certain prominent words or phrases, such as “educational and training approaches” and ”technological solutions,” emerged from the data. These were revisited to determine whether they encapsulated key patterns within the data and aligned with the research questions. This phase involved identifying what made each theme distinctive and assigning a name that reflected its core essence. The names for each theme and sub-theme were directly derived from the language used in the articles. The analysis of themes revealed diverse approaches to addressing IO across 4 main categories and 9 subthemes, as illustrated in Figure 6.4. Appendix H includes a worked example that demonstrates how raw data were coded and systematically developed into themes.

Figure 6.4: Classification of Strategies for Managing Information Overload



A description of the main themes representing strategic approaches for managing IO, as identified via thematic analysis, is presented in Table 6.3.

Table 6.3: Description of Strategies for Managing Information Overload

Strategy Theme	**Description**
Personal Strategies	Actions individuals take to regulate their own information intake and reduce cognitive burden. Examples include filtering inputs, selectively attending to priority sources, withdrawing from non-essential channels, and employing deliberate avoidance techniques.
Organisational & Technological Solutions	System-level and tool-based interventions that streamline, organise or personalise information flows. This includes interactive dashboards, algorithmic filtering, recommendation engines, automated summarisation, and other platform features designed to surface only the most relevant content.
Educational & Training Approaches	Skill-building initiatives to enhance users' ability to navigate rich digital environments. Key elements are information literacy programs, hands-on training in digital tool use, critical evaluation workshops, and guided practice in effective search, filtering, and information-management techniques.
Communication & Information Sharing	This theme addresses the need for clearer, more efficient structures and policies for how information is communicated and shared within an institution or learning environment to reduce overload burden, including policy adjustments and simplification of information delivery.

6.4 Personal Strategies

Personal strategies are vital for individuals to manage IO by focusing on relevant information and minimising exposure to excessive sources. Key personal strategies include filtering, selective attention, withdrawal, escape, and avoidance (Bawden and Robinson, 2020; Eppler and Mengis, 2008; Johnson, 2014; Savolainen, 2007; Schmitt et al., 2018).

6.4.1 Filtering and Selective Attention

Johnson (2014) discussed selective attention as a strategy similar to filtering, emphasising the importance of knowing when to stop seeking and filter relevant information amid overwhelming information influxes.Savolainen (2007) identified filtering and withdrawing as primary strategies for managing IO among environmental activists. The first filtering strategy operates at the level of information content, involving systematic efforts to eliminate irrelevant data from selected sources. For instance, this might include deleting emails based on the subject line or the correspondent, a process that involves concentrating on the most relevant information.

6.4.2 Filtering and Withdrawing

The second withdrawal strategy operates at the level of information sources. Its goal is to minimise the number of information sources to protect oneself from IO. This can involve, for instance, choosing only reliable sources of information (Savolainen, 2007). Similarly, Bawden and Robinson (2020), Shachaf et al. (2016), and Jones and Kelly (2018), identify information withdrawal as a major strategy for managing IO. Additionally, Saxena and Lamest (2018) observed that managers seeking to tackle this issue often employ a combination of personal strategies, including filtering, withdrawal, and summarising techniques.

Examples of withdrawal: A student customises their learning platform settings to limit notifications, only receiving alerts for essential updates and assignments. They also choose to temporarily disable or mute notifications from non-essential educational apps and forums, and they set aside specific times for checking these tools to avoid constant interruptions. Additionally, the student might focus exclusively on content that aligns with their current coursework or academic goals, avoiding unrelated resources that could contribute to IO. If the student feels overwhelmed, they might even take a break from certain digital learning tools or platforms for a period to regain focus and reduce IO.

6.4.3 Escape and Avoidance Strategies

Sweeny et al. (2010) describes escape as a strategy to avoid IO, which involves behaviours aimed at preventing or delaying the acquisition of available but potentially unwanted information. Similarly, Manheim (2014) contends that refraining from seeking information can be a reasonable measure in certain situations, as it will certainly prevent or at least minimise overload. Moreover, Johnson (2014) highlights that avoidance or escape can be a perfectly rational response to IO when the acquired information is not useful.

6.5 Organisational and Technological Solutions

6.5.1 Information Systems and Dashboards

In the realm of information systems, interactive dashboards have emerged as powerful tools for managing big data. Saxena and Lamest (2018) examined the application of interactive dashboards in the hospitality sector and found that, to cope with information overload, managers at the organisational level evolved the practice of summarising information into the development and use of interactive dashboards. Alhamadi (2020) emphasise interactive dashboards that are effective tools for summarising data and mitigating IO through the application of effective visualisation establishes. They enhance performance, streamline business operations, support strategic decision-making, facilitate the integration of institutional data with decision-making practices, improve routine monitoring, track process effectiveness, and reduce data complexity.

6.5.2 Algorithms and Recommender Systems

The emphasis is on the improved system, which has the ability to anticipate a user's future preferences for a variety of items. Additionally, it filters through resources to present the most relevant information. In the recommender systems literature, several studies have highlighted how modelling users' affective, behavioural, and semantic signals can improve the relevance and personalisation of recommendations while helping to manage information overload (Arapakis et al., 2009a,b; Moshfeghi and Jose, 2011; Moshfeghi et al., 2009; Paun et al., 2023). Kozko and Melnikov (2016) proposed adaptive educational forums for efficient information management; this platform offers features that address IO. It provides resources on common approaches and algorithms for platform evaluation and optimisation based on user data.

Turetken and Sharda (2004) introduced a visualisation algorithm to manage IO in web search results, aiming to develop a system that utilises clustering and visualisation to reduce the amount of data retrieved during a search. Huang et al. (2024) proposed a personalised guide recommendation system to mitigate IO by using association rule mining to discover guide recommendation rules based on visiting behaviours. Porcel et al. (2010) introduced an improved recommender system aimed at tackling the persistent problem of IO in a university digital library. This system features a memory component that tracks resources previously not recommended to the user. As a result, it can include these resources in future recommendations, especially when resource suggestions are scarce or when the user seeks a blend of previously chosen resources. Jia and Wang (2021) proposed several solutions for college students, including credible information filtering platforms, increased psychological support, psychological assistance services, and information search courses to manage IO.

Kang and Chung (2022) tackled the problem of IO by aiding users in discovering relevant content. It introduces a novel approach that employs a preference tree to predict user preferences in real-time. This method enhances accuracy and offers fresh content recommendations, surpassing the performance of existing systems.

Zhu and Sun (2023) explored a strategy for education management using a personalised information push system based on recommendation algorithms. This system tailors learning resources for instructors and learners by analysing their usage history and tags, ensuring data accuracy through pre-processing and reducing the volume of unnecessary information. Incorporating clustering algorithms enhances computing efficiency while optimising collaborative filtering with information entropy and standard deviation improves recommendation accuracy. These measures collectively help in managing and mitigating IO by ensuring that users receive personalised, relevant, and manageable amounts of information.

6.6 Educational and Training Approaches

6.6.1 Information Literacy and Education

Hartmann and Weibenberger (2024) explored the importance of information literacy instruction in addressing information IO among academic librarians. They emphasised that enhanced research skills enable users to improve their search capabilities effectively. Ellwart et al. (2015) presents a structured online team adaptation procedure to help virtual teams mitigate IO through awareness, collective awareness, and plan formulation. Cheuk (2008) proposed that information literacy is a crucial aspect of human resource development encompassing four dimensions: first, the adept use of information at a strategic level; second, the organization and management of information; third, knowledge of access methods and tools; and fourth, the integration of information retrieval with its application.

6.6.2 Training and Skill Development

Soucek and Moser (2010) demonstrated that training can improve information processing to prevent IO at the individual level, particularly in email communication. The study showed that training interventions enhance the ability to process incoming emails and alleviate stress related to email communication Soucek and Moser (2010). Stadin et al. (2020) recommended training to enhance individual strategies and competencies in managing emails and software usage, as well as promoting effective communication practices and reliable IT support.

Similarly, a meta-analysis by Ellwart and Antoni (2017) highlighted that individuals can effectively process a substantial amount of information when they possess the necessary skills to use advanced technology. These competencies should be developed through ongoing education, such as providing educators and learners with training in the use of prerequisite technologies. Benselin and Ragsdell (2016) noted that consistent training and guidance can mitigate IO, leading to enhanced productivity and increased job satisfaction. This aligns with Cheng and Vassileva (2006), who found that training employees in effective email management can save time and improve overall productivity.

Although Ellwart and Antoni (2017) and related studies emphasise the benefits of training in increasing individuals' capacity to process information, the findings of this thesis indicate a more nuanced picture. In digital learning environments, where students face not only large volumes of information but also rapidly changing technologies, fragmented platforms, and diverse sources of content, the positive effects of skill and training appear to reach a threshold. The results of this research showed that even students with higher levels of technology self-efficacy experienced increased digital fatigue under conditions of content overload. This suggests that skills and training are necessary but not sufficient to fully eliminate IO in dynamic, unstructured learning contexts. Instead, they should be viewed as moderators that help delay or reduce overload, rather than as guarantees of its prevention.

6.7 Communication and Information Sharing

6.7.1 Cultural and Policy Adjustments

Lauri et al. (2021) propose that higher-education institutions can mitigate IO by establishing clear information-culture policies, fostering balanced communication, and facilitating horizontal information sharing. Their empirical findings demonstrate that these measures reduce staff perceptions of overload by:

- Developing clear information-culture policies – defining how information is valued, managed, and accessed within the institution to eliminate ambiguity and streamline resource discovery.
- Balancing communication channels – optimizing e-mails, meetings, and announcements so that messages are concise, relevant, and delivered to the right audiences, thereby reducing cognitive load.
- Enhancing horizontal information sharing – promoting direct collaboration and information exchange across teams and units to remove hierarchical bottlenecks and accelerate access to needed information.

In essence, these recommendations aim to create a more organised, efficient, and collaborative information environment, thereby reducing the feeling of being overwhelmed by the sheer volume or disorganisation of information faced by academic staff.

6.7.2 Recommendations and Simplified Information

Koen et al. (2018) suggested simplified nutrition information, more graphics, and less textual content to reduce IO for consumers in the healthcare sector. Clarke et al. (2013) highlighted the need to understand the information needs of physicians and nurses to enhance patient care efficiency and reduce IO caused by the widespread adoption of electronic health.

6.8 Summary of Chapter

This chapter presents a systematic review of 38 cross-disciplinary studies, conducted in accordance with the PRISMA guidelines for systematic reviews, to explore key strategies for managing IO. Thematic analysis revealed four major themes: personal strategies, which focus on individuals' abilities to filter, prioritize, and manage information; organizational and technological solutions, highlighting the use of systems and digital tools to streamline and personalize information delivery; educational and training approaches, emphasising the importance of information literacy and skill development to better navigate digital environments; and communication and information sharing, which addresses the need for clearer, more efficient communication structures to reduce cognitive burden. Based on the emergent findings, the developed conceptual framework and its implications are discussed in the following chapter.

Chapter 7

Discussion

7.1 Introduction

Chapters 5 and 6 presented the main findings concerning the testing of the developed conceptual framework (using the online questionnaire) and the results of a systematic review on strategies for mitigating IO, in the serial order in which these phases were conducted, to address the research objectives:

- To develop a conceptual framework for IO within the context of DLTs through literature integration, serving as the foundational theoretical structure underpinning the investigation into RQ1, RQ2, and RQ3.
- To empirically test this conceptual framework model via a questionnaire to address RQ1 (identifying IO dimensions), RQ2 (determining associated DLT characteristics), and RQ3 (assessing the influence of digital fatigue on perceived academic performance).
- To conduct a systematic review of existing literature to determine IO management strategies (thereby answering RQ4).

Based on the Person-Environment (P-E) fit model and the Transactional-Based Theory of Stress (TBTOS) stress theory, this research proposed a model with four key components: DLT characteristics (triggers), IO dimensions (stressors), digital fatigue (strain),

and perceived academic performance (outcomes). Technology self-efficacy was examined as a moderator. Additionally, this research included a systematic review exploring a diverse range of approaches aimed at preventing or alleviating IO. The reviewed studies offer various strategies for managing IO for individuals.
There were five main findings from this research, as elaborated upon below:

- Predictors of strain.
- Digital learning tools characteristics as triggers to stressors.
- Strain and outcome.
- The role of technology self-efficacy as a moderator.
- Strategies for dealing with information overload.

7.2 Conceptual Framework Test Finding Discussion

7.2.1 Predictors of strain

Chapter 4 posits that IO (i.e., stressors) serves as a core determinant of digital fatigue (i.e., strain), and the conceptual framework assumes that strain is a direct response to these stressors. Demonstrating this link is therefore a crucial outcome of this research. As shown in Chapter 5, after confirming measurement reliability and validity and ruling out multicollinearity (VIFs 1.04–2.60; all < 3), the structural model indicates that the four overload dimensions collectively explain a substantial proportion of variance in digital fatigue ($R^2 = 0.581$; adjusted $R^2 = 0.572$; see Table 5.6). In other words, 58% of the variability in strain is accounted for by content, communication, social, and system features overload, underscoring their central role in shaping students' fatigue in digital learning environments. This finding supports the set of hypotheses H5a–H5d, which individually propose that each of these overload dimensions is positively associated with digital fatigue. The strongest contributor to strain in this sample was content overload. The next strongest predictors were system features overload and social overload, which exhibited similar path coefficients. Contrary to expectations, communication overload did not significantly relate to strain.

Content overload emerged as the strongest predictor of digital fatigue ($\beta = 0.422$, $t = 5.205$). A one standard deviation increase in content overload corresponds to a 0.42 SD increase in fatigue. This suggests that when students face large volumes of learning material, redundant resources, or difficulty filtering relevant content, their cognitive resources are depleted, leading to exhaustion. These findings align with prior research highlighting the detrimental impact of excessive information on cognitive processing and well-being (Al Abdullateef et al., 2021; Lee et al., 2016a; Xiao and Mou, 2019; Zhang et al., 2016). From the perspective of the person-environment fit framework, this can be seen as a disconnect between the environmental demands and the students' skills and capacities to effectively cope with these demands. Therefore, students' ability to maintain focus amid the constant influx of information and manage competing demands emerges as a substantial challenge.
Similarly, System features overload also significantly predicted fatigue ($\beta = 0.243$, $t = 3.075$) . This indicates that perceived complexity and feature bloat in digital learning tools meaningfully elevate strain. These results are consistent with previous studies showing that complex system interfaces and frequent feature updates increase user frustration and fatigue (Karr-Wisniewski & Lu, 2010; Fu et al., 2020; Lee et al., 2016a). From a Person–Environment Fit perspective, this reflects a misalignment between students' abilities and the demands imposed by dynamic, feature-rich platforms (Cooper et al., 2013).

Social overload was another significant predictor ($\beta = 0.200$, $t = 3.041$). This suggests that excessive social demands, such as constant participation in group discussions and peer interactions, contribute to student exhaustion. This finding aligns with Maier et al. (2012) and Zhang et al. (2016), who reported that persistent social interaction pressures in online environments amplify stress and fatigue, particularly when students feel expected to maintain continuous presence and responsiveness.

By contrast, communication overload did not significantly predict fatigue ($\beta = 0.004$,

$t = 0.052$). This diverges from earlier studies that identified communication demands as a major stressor (Al Abdullateef et al., 2021; Lee et al., 2016a). A plausible explanation is that students have developed coping strategies, such as filtering, batching, or prioritising messages, that mitigate the cognitive burden of communication. Alternatively, communication tasks may require less cognitive effort compared to processing dense content or navigating complex systems, reducing their incremental effect on fatigue.

7.2.2 Digital Learning Tools Characteristics as Triggers to Stressors

The suggested conceptual framework posits that DLTs amplify the misfit between person and environment, thereby introducing a set of stressors specifically linked to DLTs. The relationship between the characteristics of DLTs and the resulting stressors is explored in the following discussion.

Triggers of Content Overload

The characteristics of DLTs, categorised under 'information characteristics' (information volume, irrelevance, and equivocality), 'communication characteristics' (hyperconnectivity), and 'engagement characteristics' (excessive interactions), were identified as potential triggers for content overload, as hypothesised in H1a, H1b, H1c, H1d, and H1e. The results indicate that these factors account for 63% of the variance in content overload.

The results indicate that information volume had the most significant impact on content overload ($\beta = 0.382$, $t = 6.115$), followed by excessive interactions ($\beta = 0.290$, $t = 4.127$) and information irrelevance ($\beta = 0.138$, $t = 2.001$). These findings align with previous research (Chen et al., 2011; Graf and Antoni, 2021; Kushnir, 2009; Lee et al., 2016a), demonstrating that the inherent demands of digital learning environments significantly contribute to increased overload. Perceptions of content overload intensified when students perceived that the demands imposed by DLTs exceeded their ability to effectively cope within the learning environment.

Furthermore, the hypothesis H1c proposed that information equivocality would significantly predict content overload. However, the results show a weak and statistically non-significant relationship ($\beta = 0.059$, $t = 0.981$). In structural equation modelling, a common threshold for statistical significance is $t \geq 1.96$ at the 5% significance level (two-tailed test) (Hair et al., 2021). Since the observed t-value (0.981) is well below this threshold, the effect of information equivocality on content overload is not statistically significant. This means that, in this study, ambiguity in information does not meaningfully contribute to content overload compared to other factors such as information volume or excessive interactions.

Consequently, the weak influence of equivocality on content overload may imply that students are either able to manage ambiguous content more effectively or that other elements of the digital learning environment play a more critical role in driving overload perceptions. The research's findings do not align with previous research (e.g., Lee et al. 2016a), which found that information equivocality was significantly and positively related to content overload. This suggests that although clarity is important, students' perceptions of overload are more strongly influenced by the sheer volume, lack of relevance, and high engagement demands of the content they encounter.

Contrary to expectations, hyperconnectivity exhibited a significant negative relationship with content overload ($\beta = -0.141$, $t = -2.925$). From the perspective of the person-environment fit framework, this unexpected finding suggests that increased connectivity may facilitate better access to information, potentially enhancing students' ability to manage their learning demands more effectively. Rather than overwhelming students, hyperconnectivity might provide opportunities for real-time collaboration, clarification, and streamlined communication, thus reducing feelings of content overload.

Triggers of Communication Overload

The conceptual framework hypothesised that communication-related characteristics of DLTs, specifically hyperconnectivity and interruptions, would significantly predict communication overload (H2a and H2b). The results indicate that these factors collectively explain 38% of the variance in communication overload.

Interruptions emerged as the strongest and most significant predictor of communication overload ($\beta = 0.526$, $t = 11.200$). This finding confirms that frequent, unscheduled notifications and demands for immediate responses disrupt students' workflow and increase perceived communication burden. These results are consistent with prior research linking interruptions to technostress and reduced task efficiency in digital environments (Conrad et al., 2022; Karr-Wisniewski and Lu, 2010; Tams et al., 2020; Webster and Watson, 2002). From the perspective of the person–environment fit framework, interruptions create a demands–abilities misfit by acting as external stimuli that disrupt task continuity and require frequent cognitive switching, thereby increasing overload and contributing to strain. .

By contrast, hyperconnectivity exhibited a negative and statistically significant relationship with communication overload ($\beta = -0.217$, $t = -3.192$). This aligns with prior research on WhatsApp, which found that constant connectivity with study groups and peers was not perceived as negative (Al Abdullateef et al., 2021). A plausible explanation is that students perceive hyperconnectivity as beneficial for maintaining control over their learning activities, enabling them to manage communication demands more effectively. Increased connectivity may facilitate timely access to information and peer support, reducing the sense of overload rather than exacerbating it.

Triggers of Social Overload

The conceptual framework hypothesised that engagement-related characteristics of DLTs, particularly excessive interactions, and communication-related characteristics such as hyperconnectivity, would significantly predict social overload (H3a and H3b). The results indicate that these factors collectively explain 32.5% of the variance in social overload.

Excessive interactions emerged as the strongest and most significant predictor of social overload ($\beta = 0.510$, $t = 8.487$). This finding suggests that high demands for social engagement—such as frequent group discussions, collaborative tasks, and peer interactions—substantially contribute to feelings of being socially overwhelmed. These results align with prior research demonstrating that persistent social interaction pressures in online environments amplify stress and fatigue (Maier et al., 2012; Zhang et al., 2016).

From a transactional stress perspective, these interactions act as continuous stimuli that require emotional and cognitive resources, thereby increasing strain.

By contrast, hyperconnectivity did not significantly predict social overload ($\beta = -0.151$, $t = -1.785$). The effect of hyperconnectivity on social overload is not statistically significant. This suggests that being constantly connected does not necessarily translate into perceived social burden when students can manage their engagement levels effectively. One possible explanation is that students may selectively engage in social interactions or use platform features to control notifications, thereby mitigating the potential negative impact of hyperconnectivity.

In general, this suggests that social overload in digital learning environments is primarily driven by the intensity of interaction demands rather than by connectivity itself.

Triggers of System Features Overload

The conceptual framework hypothesised that dynamic characteristics of DLTs, specifically pace of change and complexity, would significantly predict system features overload (H4a and H4b). The results indicate that these factors collectively explain 35.6% of the variance in system features overload.

Complexity emerged as the strongest and most significant predictor of system features overload ($\beta = 0.594$, $t = 11.987$). This finding suggests that when students perceive DLTs as highly complex—requiring substantial effort to navigate and operate—they experience a greater sense of overload. From the perspective of the person–environment fit framework, this reflects a clear demands–abilities misfit: the cognitive and technical demands imposed by complex systems exceed students' available skills and resources, thereby increasing strain. These results are consistent with prior research demonstrating that feature-rich platforms and intricate interfaces elevate technostress and fatigue (Fu et al., 2020; Karr-Wisniewski and Lu, 2010; Lee et al., 2016a).

By contrast, pace of change did not significantly predict system features overload ($\beta = 0.011$, $t = 0.161$). The effect of pace of change on system features overload is not statistically significant. This suggests that frequent updates and modifications to DLTs do not substantially contribute to overload in this context. A plausible explanation is that students have become accustomed to continuous updates in digital platforms, reducing their disruptive impact compared to earlier research contexts (Lee et al., 2016a). Instead, it is the inherent complexity of the system, rather than the speed of change, that drives perceptions of overload.

7.2.3 Strain and Outcome

The conceptual framework hypothesised that digital fatigue (strain) would negatively influence students' perceived academic performance (H7). The structural model results strongly support this hypothesis, indicating a significant negative relationship between digital fatigue and perceived academic performance ($\beta = -0.468$, $t = 7.345$). This means that as students experience higher levels of fatigue resulting from digital learning tools, their self-assessed academic performance declines. From the perspective of the person–environment fit framework, this relationship reflects a clear demands–abilities misfit: when the cognitive and emotional demands imposed by digital learning environments exceed students' coping resources, strain manifests as fatigue, which in turn undermines their ability to achieve desired academic outcomes. This finding aligns with prior research demonstrating that technostress and fatigue negatively affect learning engagement and performance in digital contexts (Al Abdullateef et al., 2021; Lee et al., 2016a; Yu et al., 2019).

The explanatory power of the model for this outcome is moderate, with digital fatigue accounting for approximately 21.9% of the variance in perceived academic performance ($R^2 = 0.219$; see Table 5.6). Although this suggests that other factors beyond fatigue also influence performance, the strong path coefficient underscores the practical significance of managing fatigue in digital learning environments. Persistent fatigue can impair concentration, reduce motivation, and increase the likelihood of disengagement, ultimately leading to poorer academic outcomes.

7.2.4 Moderator Hypothesis Discussion

The findings reveal that technology self-efficacy plays a moderating role in the relationship between information overload IO and digital fatigue, though in a more complex manner than originally hypothesised.

Specifically, the interaction between *content overload* and *technology self-efficacy* was found to be statistically significant, with a path coefficient $\beta = 0.183$, $t = 2.430$. This indicates that as students' technology self-efficacy increases, the relationship between content overload and digital fatigue becomes stronger, not weaker as initially expected.

This counterintuitive result suggests that students with higher technological competence may engage more deeply with digital content—taking on more complex tasks, managing larger volumes of online materials, and utilising advanced features of digital platforms. This deeper engagement may inadvertently lead to greater cognitive load, exhaustion, and decreased productivity, thereby amplifying digital fatigue.

To illustrate this moderation effect, a simple slope analysis using standard deviation (SD) values was conducted:

- At **average self-efficacy** (mean level): Effect of content overload on digital fatigue $= 0.422$
- At **high self-efficacy** (+1 SD): Effect $= 0.422 + 0.183 = 0.605$
- At **low self-efficacy** (-1 SD): Effect $= 0.422 - 0.183 = 0.239$

These figures show that students with higher self-efficacy (+1 SD) experience a stronger impact of content overload on digital fatigue, while those with lower self-efficacy (-1 SD) experience a weaker impact. This quantifies how changes in self-efficacy levels influence the strength of the overload-fatigue relationship.

In contrast, the moderating effects of technology self-efficacy on the relationships between other IO dimensions and digital fatigue were statistically insignificant:

Communication overload and digital fatigue ($\beta = -0.062$, $t = -0.640$), Social overload and digital fatigue ($\beta = -0.015$, $t = 0.212$) , and System feature overload and digital fatigue ($\beta = -0.057$, $t = -0.801$). These results indicate that technology self-efficacy does not significantly buffer the effects of these overload dimensions on digital fatigue.

Interestingly, prior research conducted in workplace settings presents contrasting outcomes. For example, studies by Delpechitre et al. (2019) found that technology self-efficacy mitigated the impact of IO-related role stress, and Yen (2022) reported that workers with high technological self-efficacy experienced less overload-induced stress. These findings suggest that while technological competence is important, it may not be sufficient on its own in academic settings. Additional mechanisms, such as information literacy training, are needed to support students in digitally intensive learning environments (Bawden and Robinson, 2020).

In essence, high self-efficacy may inhibit students from strategically disengaging when information volume exceeds a manageable threshold, thereby increasing their susceptibility to burnout from content overload. This contrasts with students possessing lower self-efficacy, who may disengage earlier or disregard excess information. These findings underscore the need for a more nuanced approach to supporting learners in digitally intensive environments.

7.3 Strategies for Dealing With Information Overload

The preceding section established that IO significantly compromises student well-being and productivity, resulting in digital fatigue and reduced academic performance. The empirical findings from this research underscore the multifaceted detrimental effects of IO. Given the urgent need for management strategies, a systematic review was undertaken to identify methods for mitigating IO. This review revealed diverse approaches, encompassing personal filtering techniques and institutional policy adjustments, which provide valuable insights for tackling IO challenges. Synthesising these insights with our empirical data, this section presents a framework aimed at managing IO and enhancing the digital learning experience.

7.3.1 Personal Strategies

The finding of content overload as a dominant stressor and excessive interactions, information volume, and information irrelevance as the key overload characteristics of DLTs, underscores the necessity of targeted interventions. One of the key coping mechanisms identified in the systematic review is information filtering and selective attention (Lauri et al., 2021; Savolainen, 2007; Saxena and Lamest, 2018; Shachaf et al., 2016). Accordingly, educational institutions should train students with respect to personal strategies to deal with these challenges. Educational institutions should also develop policies that encourage students to adopt personal filtering strategies, which are essential for managing the overwhelming volume of information encountered in DLTs. These strategies, such as selectively attending to relevant information and filtering out irrelevant or distracting stimuli, enable students to prioritise their learning and minimise IO. For instance, Blocker (2011) emphasised the need to prevent IO among students, noting that efficient filtering is crucial in this process. By streamlining information access, filtering enhances student satisfaction with digital learning platforms and promotes their continued engagement. The instructor's actions directly empower the student to effectively implement the selective attention and filtering strategy. To help students navigate course content more effectively, instructors can clearly distinguish essential materials from optional resources. This can be achieved by creating a prioritised list, using visual markers such as asterisks or colour coding, or categorising materials by levels of importance. By implementing these strategies, instructors can reassure students, reduce IO, and enhance their ability to focus on critical learning objectives (Chen, 2003). Furthermore, to mitigate content overload resulting from excessive interactions, educational institutions could implement policies that discourage constant connectivity. Bawden and Robinson (2020) highlight a key withdrawal strategy: customising notification settings. By adjusting these settings on their DLTs to limit non-essential notifications, unsubscribing from irrelevant forums, disabling alerts during study periods, and muting non-urgent messages, students can minimise distractions and concentrate more effectively on essential coursework, thereby reducing overload. For example, educational institutions could advise students to designate specific times during the day for checking digital notifications rather than continuously monitoring them.

Instructors play a crucial role in mitigating IO within the learning environment and can employ several strategies to support students. To help students navigate course content effectively, instructors can clearly distinguish essential materials from optional resources. This can be achieved by creating a prioritised list, using visual markers such as asterisks or colour-coding, or categorising materials by levels of importance. By implementing these strategies, instructors can reassure students, reduce IO, and enhance their ability to focus on critical learning objectives (Chen, 2003).

The success of personal coping strategies relies on individuals' cognitive resources and their ability to effectively apply these strategies consistently. However, limited cognitive capacity and the complexities of the modern information environment can hinder the successful application of these strategies. This highlights the importance of organisational and technological interventions to assist students in navigating the challenges of IO.

7.3.2 Organisational and Technological Solutions

Given the significant impact of information volume and irrelevance on content overload—and the effect of system complexity on system features overload, as demonstrated in this study—technological solutions such as interactive dashboards, filtering algorithms, and recommender systems are crucial for creating a more manageable and efficient digital learning environment (Jian et al., 2022; Kang and Chung, 2022; Khalid et al., 2021; Lei et al., 2022; Voinea et al., 2020; Zhu and Sun, 2023). These technologies play a vital role in organising, structuring, and personalising digital content by filtering out irrelevant information, presenting key data in a clear and concise format, and recommending relevant resources based on individual student needs. Prior work on recommender systems and interactive retrieval has shown that such technologies can both alleviate and inadvertently exacerbate overload, depending on how user preferences, affect, and cognitive constraints are modelled (Moshfeghi and Jose, 2011; Moshfeghi et al., 2009, 2011; Paun et al., 2023). More recent work on auditing and governing AI-driven systems further emphasises the need for transparent and bias-aware mechanisms when deploying personalised and automated filtering in high-stakes environments (Azzopardi and Moshfeghi, 2024, 2025; Stumpf et al., 2025). This approach can help students to:

- **Reduce cognitive load**: minimise the amount of information students need to process by filtering out irrelevant data.
- **Improve focus**: direct students' attention to the most relevant and important content, helping them avoid distractions.
- **Enhance learning efficiency**: provide easy access to the necessary resources, simplifying navigation and optimising the learning process.

For example, personalised information push algorithms enhance data fidelity through pre-cleaning and preprocessing techniques. Advanced recommendation techniques can enhance the relevance of suggested content, reducing unnecessary information and supporting more efficient learning. Furthermore, collaborative filtering technology refines the recommendation process by analysing user interactions and preferences, ensuring that students receive tailored learning resources aligned with their academic interests and information needs (Kang and Chung, 2022; Zhu and Sun, 2023).

Moreover, interactive dashboards address system features overload by centralising essential academic data—such as assignments, grades, webinars, quizzes, schedules, and announcements—into a single, easy-to-navigate interface. Customisable views allow students to focus on what is most relevant, while visual representations like charts and progress bars simplify complex data. Interactive elements (e.g., filters and expandable sections) further enable students to access specific information without feeling overwhelmed (Saxena and Lamest, 2018).

By reducing IO and improving the usability of digital learning tools, these technologies can enhance the student experience by fostering a more engaging and effective learning environment. This, in turn, can lead to enhanced academic performance. While personal strategies and technological solutions offer valuable approaches to managing IO, their effectiveness can be further enhanced through targeted educational and training interventions.

7.3.3 Educational and Training Approaches

Educational and training approaches, including information literacy programs and structured skill development in digital literacy and information management, are essential mechanisms for mitigating IO (Bawden and Robinson, 2020; Lauri et al., 2021). Enhancing information literacy skills is recognised as an effective approach to alleviating the effects of IO (Lauri et al., 2021). Information literacy encompasses a diverse range of skills that empower individuals to navigate the digital world effectively. These skills can be broadly categorised into five core areas, as outlined by Robinson and Bawden (2018) in their framework for information literacy:

- Understand and participate in digital activities.
- Locate information.
- Critically assess information, interactions on digital platforms, and online resources.
- Handle and convey information.
- Work collaboratively and distribute digital content.

These five core areas are crucial for navigating the complexities of the digital world and managing IO. Research suggests that strengthening information literacy skills may be a viable strategy for mitigating the effects of IO (Bawden et al., 1999; Lauri et al., 2021). This supports the notion proposed by Oliver (2017) that a strategic approach to information literacy development can empower individuals to take greater ownership of their information literacy skills, thereby improving their ability to cope with the challenges of IO. These must go beyond simply teaching students how to use DLTs and instead focus on developing the cognitive and search skills necessary to navigate the complex digital learning environment. The empirical results of this research revealed a crucial insight:

students with high technology self-efficacy did not experience lower content overload, and in some cases, high technology self-efficacy was associated with increased overload. This reinforces the need for educational interventions that address the cognitive burden associated with IO rather than merely enhancing technical proficiency. As discussed in "Moderator Hypothesis Discussion" (section 7.2.4), highly self-efficacious students may be more prone to overcommitment and increased cognitive effort when faced with content overload, ultimately leading to greater digital fatigue.

For example, critically evaluating information, online interactions, and digital tools for relevance and reliability against learning needs is central to complex DLT environments. This ongoing assessment directly guides how students seek and use information, which digital tools they employ, and how they interact online. Developing this critical aspect of information behaviour empowers students to better manage potential overload and ultimately use DLTs to effectively achieve their academic goals.

By equipping students with essential information literacy skills through targeted workshops, seminars, and hands-on training sessions—and by raising awareness about the risks of IO and the importance of digital well-being—educational institutions can empower them to effectively navigate the complexities of the digital learning environment, minimise the negative impacts of IO, and ultimately enhance their overall learning experience. While robust educational and training approaches provide valuable strategies for managing IO, their effectiveness can be further enhanced through targeted improvements in communication and information sharing.

7.3.4 Communication and Information Sharing

Effective communication and information sharing are critical for managing IO in digital learning environments. Cultural and policy adjustments—such as establishing formalised communication protocols and clear guidelines for information exchange—can simplify the way information is shared and processed. While Lauri et al. (2021) focused on academic staff, their findings offer insights that can be extended to students in digital learning environments. In a formal information-sharing setting, students benefit from structured, reliable communication—such as official announcements, curated course materials, and scheduled lectures—that helps streamline the flow of critical academic content. This organised approach minimises ambiguity and ensures that students receive consistent, high-quality information, which can significantly reduce IO.

On the other hand, informal information sharing—through peer discussions, study groups, and social media interactions—provides opportunities for immediate, context-specific support and collaborative learning. These informal channels can foster a sense of community and encourage a spontaneous exchange of ideas, which is particularly valuable for problem-solving and reinforcing learning. However, if not properly managed, informal channels may contribute to IO by inundating students with non-essential or redundant information. A balanced approach that integrates both formal and informal communication strategies can be highly beneficial. For example, educational institutions could maintain centralised, formal channels for distributing key course information while also encouraging moderated, peer-to-peer interactions that allow students to engage and collaborate effectively. By establishing clear guidelines for both types of information sharing, institutions can help students filter out noise, focus on what's important, and ultimately enhance their overall learning experience.

Based on these findings, educational institutions should prioritise the development and implementation of strategies that address IO, including providing training on information literacy and promoting the use of technology-enhanced tools for managing information flow. A complementary direction for future work is the integration of neuroscientific and brain–computer interface (BCI) approaches into the study of IO in digital learning environments. Research in neuro-information retrieval has demonstrated that neural and physiological signals, captured using fMRI and EEG, can be used to characterise relevance judgements, the realisation of information need, satisfaction, and mental workload during complex search and decision-making tasks (Kingphai and Moshfeghi, 2025; Moshfeghi and Pollick, 2019; Moshfeghi et al., 2013, 2016; Paisalnan et al., 2023; Pinkosova et al., 2020). Applying similar methods to DLT contexts could enable the development of adaptive systems that monitor early signs of cognitive strain and overload, adjust the timing and volume of information delivery, and ultimately support student well-being and sustained engagement.

7.3.5 Successful Responses to Information Overload

Recent research and practice highlight a range of empirically supported strategies that effectively mitigate IO and its associated strains, such as technostress and digital fatigue, in technology-rich learning environments. These responses operate across personal, technological, pedagogical, and organisational levels.

- **Individual-Level Strategies:** Evidence from the undergraduate students at a major public university in the United Arab Emirates study demonstrates that coping mechanisms—particularly those aimed at reducing platform scope, limiting usage time, and prioritising educational platforms—are positively associated with improved student engagement. These findings reinforce the importance of personal strategies such as avoidance, withdrawal, filtering, and queuing, which align with established information overload literature (Tafesse et al., 2024).

- **Technological Solutions:** Educational technology teams have successfully implemented tools that streamline information delivery and reduce fragmentation. Examples include interactive dashboards that consolidate course data, personalised recommendation systems that prioritise essential content, and algorithmic filtering features that minimise irrelevant information (Jian et al., 2022; Khalid et al., 2021; Wang, 2022). Platforms that provide weekly digests instead of multiple alerts have also been shown to reduce perceived overload by creating predictable communication rhythms.

- **Educational and Training Approaches:**

Strengthening students' information literacy through targeted workshops and integrated course modules has proven effective in reducing cognitive strain and improving their ability to manage complex digital environments. Embedding library-led sessions on research strategies within curricula equips learners with essential skills to filter, evaluate, and organise digital content efficiently. At the institutional level, universities can play a pivotal role by providing structured guidance and training, implementing digital well-being programmes, and incorporating coping strategies into digital and information literacy curricula (Lauri et al., 2021; Tafesse et al., 2024).

Organisational Policies and Communication: Institutions play a pivotal role in shaping communication practices that minimise IO. Effective measures include consolidating announcements, aligning assignment deadlines, and issuing a single weekly update rather than multiple fragmented messages. During the COVID-19 transition to remote learning, universities that emphasised structured course design and clear, empathetic communication reported lower student anxiety and reduced information fatigue. Establishing clear communication guidelines for instructors—such as limiting email volume and setting uniform response expectations—further reduces cognitive load (Mostafa and Bali, 2021).

Collectively, these examples demonstrate that successful responses to IO require coordinated interventions across individual, technological, pedagogical, and organisational domains. The recommendations proposed in this thesis build on these proven strategies and extend them through a multi-stakeholder framework that integrates information literacy as a core competency for sustainable digital learning environments.

7.4 Chapter Summary

This chapter synthesises findings from two research phases: first, an online questionnaire testing a conceptual model, which demonstrated that IO in DLTs significantly contributes to student digital fatigue and negatively impacts perceived academic performance; and second, the chapter integrated these empirical insights with the systematic review findings, discussing a range of personal (e.g., filtering), technological (e.g., recommender systems), educational (e.g., information literacy), and communication and information sharing strategies to mitigate the challenges of IO in the context of DLTs.

Chapter 8

Conclusion

8.1 Chapter Preview

This research aimed to investigate the IO induced by DLTs from an Information Science perspective and examines its effects on digital fatigue and higher education students' perceived academic performance in the UK. There were four main research questions:
RQ1: What are the IO dimensions that contribute to digital fatigue?
RQ2: What characteristics of DLTs are associated with each IO dimension?
RQ3: What is the influence of digital fatigue correlated with DLTs use on students' perceived academic performance?
RQ4: What strategies are used to manage or alleviate IO?

8.2 Achievement of the Research Aim and Research Questions

The research aims and questions were achieved through the following three objectives:

- **Objective 1:** *To develop a conceptual framework for IO within the context of DLTs through literature integration, serving as the foundational theoretical struc-*

ture underpinning the investigation into RQ1, RQ2, and RQ3.

This objective was achieved through a conceptual framework for IO was developed through a literature review in the context of DLTs, as presented in Chapter 4. The review identified four distinct dimensions of IO within DLTs: content overload, communication overload, social overload, and system feature overload. Additionally, it highlighted specific characteristics of DLTs that trigger each overload dimension, namely: information characteristics, communication characteristics, engagement characteristics, and dynamic characteristics.

The framework seeks to establish a connection between different forms of IO and the experience of digital fatigue, examining how specific types of overload contribute to fatigue. Furthermore, it explores the impact of digital fatigue, resulting from DLT use, on students' academic outcomes, assessing whether fatigue negatively influences performance.

Based on these insights, a conceptual framework was established, hypothesising how these characteristics contribute to different types of overload, which in turn lead to digital fatigue and impact perceived academic performance. This phase provided the theoretical foundation for subsequent empirical testing and is presented in Chapter 5.

- **Objective 2:** *To empirically test this conceptual framework model via a questionnaire to address RQ1 (identifying IO dimensions), RQ2 (determining associated DLT characteristics), and RQ3 (assessing the influence of digital fatigue on perceived academic performance).*

This objective was achieved using a quantitative approach via an online questionnaire. Two hundred undergraduate students from higher education institutions participated in the UK. The analysis of the collected data empirically tested the hypotheses developed in the first phase and provided further insights into the tangible impact of IO on students' well-being and perceived academic performance within the context of DLTs. These were presented in Chapter 5. This phase, which highlighted the significant impact of IO, laid the groundwork for the development of subsequent information management strategies.

- **Objective 3:** *To conduct a systematic review of existing literature to determine IO management strategies (thereby answering RQ4).*

This objective was achieved through a qualitative approach—a systematic review of 38 articles. The data were analysed using directed thematic analysis, and the findings are presented in Chapter 6. This analysis identified four key themes and nine subthemes, categorising various strategies for managing IO, as follows:

1. Personal strategies

- **Filtering and selective attention**: Prioritising relevant information while ignoring unnecessary content.

- **Filtering and withdrawing**: Actively reducing digital engagement by limiting interactions with overwhelming sources.

- **Escape and avoidance strategies**: taking breaks or stepping away from digital tools to reduce IO.

2. Organisational and technological solutions:

- **Information systems and dashboards:** Implementing structured platforms to streamline and organise digital content.

- **Algorithms and recommender systems:** These tools are used to prioritise and suggest relevant information, reducing overload.

3. Educational and training approaches:

- **Training and skill development:** Enhancing students' ability to manage digital tools effectively.

- **Information literacy and education:** Teaching students how to evaluate, process, and manage digital information efficiently.

4.Communication and information sharing:

- **Cultural and policy adjustments:** Establishing institutional policies to manage the *effective* sharing of information, and reduce excessive information flow.
- **Recommendations and simplified information:** Presenting information concisely and in a structured manner to improve accessibility.

The current chapter summarises the key findings and outcomes of this study, identifying its strengths and contributions to knowledge, and implications for practice, while acknowledging its limitations. This chapter concludes with a set of recommendations and suggestions for future work.

8.2.1 Summary of Key Findings

This research offers new insights into the phenomenon of IO in digital learning environments and its impact on student well-being and academic performance. The key findings are summarised below:

A Novel Conceptual Framework for Information Overload

The research introduces a new multidimensional framework that reconceptualises IO as comprising four distinct dimensions: content overload, communication overload, social overload, and system features overload. This framework integrates the Person–Environment Fit Model and the Transactional-Based Theory of Stress, offering a dynamic and theoretically grounded approach to understanding how DLTs contribute to cognitive strain.

Information Overload Triggers

The study identified specific features of DLTs that contribute to IO. These include the sheer volume of information, interruption, information irrelevance, system complexity, and excessive interactions. The study found that when students perceive digital learning platforms as difficult to navigate or excessively interactive, they are more likely to experience content overload, social overload, and system feature overload. Additionally, the constant stream of notifications and updates can lead to cognitive strain, making it harder for students to focus and prioritise information.

Detrimental Effects of Information Overload

The research demonstrated that students experience IO when using DLTs, resulting in significant adverse effects on their well-being and perceived academic performance. Specifically, IO was found to be a significant factor in exacerbating digital fatigue among students. This digital fatigue, in turn, directly impaired students' perceived academic performance. Continuous digital engagement overwhelmed students, diminishing their ability to concentrate and retain information, ultimately leading to decreased academic performance outcomes.

The Double-Edged Sword of Technical Skill

An unexpected finding concerns the role of technology self-efficacy. Contrary to assumptions that higher technical competence would mitigate IO, the results indicate the opposite. Students with high self-efficacy were more susceptible to the negative effects of content overload, as their confidence often led to over-engagement with digital resources. This over-engagement, in turn, intensified digital fatigue and increased the risk of burnout. This paradox suggests that technical skill alone is insufficient as a protective factor and may even exacerbate IO under certain conditions.

Strategies for Dealing With Information Overload

This research revealed a variety of strategies and provided insights into existing prevention and intervention measures for IO, systematically organsied into four broad themes and nine specific subthemes. Spanning personal coping techniques (e.g., filtering, withdrawal), organisational and technological interventions (e.g., dashboards, algorithms), educational and training approaches (e.g.,information literacy), communication, and information sharing like cultural and policy adjustments. These findings, as summarised in Table 8.1, add more depth to our understanding of IO and its impacts. Strategies were provided to address these challenges and support effective information management in UK higher education institutions.

Table 8.1: Summary of key findings

Novel Conceptual Framework for Information Overload
Introduced a multidimensional framework that reconceptualises IO. The framework integrates the P-E fit Model and TBTOS to explain how DLT characteristics trigger overload and affect student outcomes.
Triggers of Information Overload
Excessive information volume, information equivocality, system complexity, interruption, and excessive engagement demands from DLTs contribute to various overload dimensions (content, communication, social, and system feature overload).
Detrimental Effects on Students
Digital fatigue resulting from IO impairs concentration and information retention, ultimately decreasing students' perceived academic performance.
The Double-Edged Sword of Technical Skill
Unexpectedly, high technology self-efficacy did not protect students from the effects of content overload. Instead, it amplified the positive relationship between content overload and digital fatigue. This suggests that confident students may be more prone to over-engagement and subsequent burnout when faced with an overwhelming volume of information.
Strategies for Dealing With Information Overload
Strategies for managing IO include developing personal approaches and employing educational techniques such as filtering, selective attention, and information literacy. Also leveraging organisational and technological solutions, such as advanced information retrieval systems.

Having synthesised the key findings, it is important to recognise the strengths of this study that underpin these insights, and its limitations that must be considered when interpreting its implications for practice, as described in the following sections.

8.3 Strengths of the Study

The current research possessed several notable strengths. Firstly, its mixed-methods approach proved particularly effective in addressing the diverse research questions. This approach provided inclusive information, enhancing understanding of the causes, impacts, and treatments of IO within the digital learning environment. This analysis offers a well-rounded view of how IO influences students within higher education.

Secondly, the research recruited a diverse sample of undergraduate participants from various academic departments and universities across higher education institutions in the United Kingdom. Most previous studies predominantly concentrated on a specific subset of participants and were limited to only one or two departments and universities.

Thirdly, the innovative application of PLS-SEM using R is a significant strength of this research, representing the first known use of this analytical approach in IO research. This methodological advancement distinguishes it from previous studies, which typically relied on SmartPLS (Fu et al., 2020; Rasool et al., 2022; Yu et al., 2019) or AMOS in SPSS (Yen, 2022; Zhang et al., 2022b).

Lastly, the incorporation of the P-E Fit Model and TBTOS Theory further strengthens the research. Prior literature has identified these frameworks as effective for predicting overload related to DLTs. Although these theories provide empirical support for the antecedents of IO on digital fatigue, they have not been used to empirically examine the subsequent impact of fatigue on outcomes (Lee et al., 2016a).

8.4 Contributions to Knowledge

This research makes several contributions to knowledge within information science, particularly concerning the understanding and conceptualisation of IO in DLTs.

Firstly, development of a novel conceptual framework. The study introduces a new multidimensional framework that reconceptualises IO as comprising four distinct dimensions: content overload, communication overload, social overload, and system features overload. This framework moves beyond the traditional view of IO as a singular construct and provides a more nuanced understanding of how different types of overload manifest in digital learning environments.

Secondly, the research advances the theoretical understanding of IO by integrating the person-environment fit model and transitional stress theory. This integration elucidates how mismatches between students' cognitive capacities and the demands imposed by DLTs result in stress and fatigue. The research rigorously examines the complex interplay between the characteristics of DLTs and multiple dimensions of IO and explicates how these stressors contribute to digital fatigue, ultimately affecting students' academic performance. The research provides robust empirical evidence of the significant effects of dimensions of IO and digital fatigue on student outcomes.

Finally, this research bridges theoretical insights and practical applications by conducting a systematic review of strategies to mitigate IO. This offers a synthesis of interventions implementable at personal, organisational, and institutional levels. Unlike previous studies that often focus primarily on identifying IO as a problem, this work moves further by categorising solutions, thereby enriching the applied contributions of information science to improving digital learning environments.

8.5 Contributions to Practice

While this research makes significant academic contributions, it also provides valuable practical insights for policymakers and educators in higher education. The research offers actionable recommendations for managing IO, which can be adopted by students and implemented by institutions. By doing so, it raises awareness of the negative consequences of IO and promotes more effective strategies for mitigating its impact.

8.5.1 Information Overload is A Tangible Phenomenon

As evidenced by the findings of this research, IO is a palpable reality. Much of the extant literature has emphasised the benefits of DLTs, but the results of this study caution that these tools can also precipitate significant IO and its associated stress. Consequently, higher education institutions should be aware of and address the potential for DLTs to contribute to overload among students.

8.5.2 A Versatile Conceptual Framework for Assessing Overload

The conceptual framework developed in this research serves as a valuable tool for assessing the extent of IO within various digital learning environments. Notably, the model is not tied to a specific technology; it can be adapted to meet the unique needs of different higher education institutions, such as universities or colleges. By focusing on one tool or a set of tools, institutions can gain deeper insights into the dominant causes of IO in their particular contexts. Such understanding is essential as a preliminary step in devising effective management aimed at mitigating the negative impacts of IO.

8.5.3 Impacts of Information Overload

The detrimental effects of IO on learning outcomes in digital environments (i.e., perceived academic performance) compel educational institutions to address two critical areas that influence student well-being and productivity .

First, the findings indicate that IO is closely linked to digital fatigue. If left unaddressed, persistent overload and the resulting fatigue can negatively impact student well-being and potentially escalate into more significant mental or physical health challenges (Conrad et al., 2022). While supporting student well-being is intrinsically valuable, these adverse effects also carry tangible consequences for institutional success. Students experiencing high levels of fatigue and stress due to overload are less likely to engage effectively with their studies, directly contributing to poorer perceived academic performance and potentially increasing the likelihood of withdrawal or drop-out. Therefore, proactively reducing overload levels is crucial not only for student welfare but also serves the institution's strategic interests in enhancing student engagement, improving academic outcomes, and boosting retention rates, thereby mitigating the significant financial and reputational costs associated with student attrition.

Second, as highlighted, students experiencing IO exhibit lower perceived academic performance and are more likely to drop out. IO undermines productivity by creating confusion, inducing fatigue, and diverting attention from essential tasks. Recognising that students represent valuable human resources and the core of the educational process, institutions should prioritise strategies to minimise IO, thereby enhancing learning outcomes and retention.

To sum up, IO in digital learning environments significantly undermines student well-being and productivity by contributing to digital fatigue and lower perceived academic achievement. Consequently, institutions must prioritise proactive strategies to mitigate these adverse effects.

8.6 Limitations

Although this research makes numerous contributions to knowledge on IO and DLTs, as described above, it has some limitations, which ought to be considered. Notably, its focus on specific service settings within a single country restricts the broader generalisability of its findings, as described below.

The first limitation of this is contextual focus. The findings are derived specifically from the examination of DLTs within higher education institutions in the UK. Consequently, these results are embedded in the unique social, cultural, and regulatory framework of the UK, which may limit their applicability to other contexts.

The second limitation of this research is that it examined DLTs in their entirety, instead of targeting a specific type or platform. This broad approach provided a deep understanding of DLTs. However, future research could benefit from focusing on a particular tool, such as mobile instant messaging platforms like WhatsApp, to gain more detailed insights.

The third limitation of this research acknowledges that control variables—such as age, non-academic usage, the number of study groups, and users' gender (Al Abdullateef et al., 2021)—may influence students' DLT preferences, a factor not explicitly addressed in the current research. Future studies should incorporate these variables into a conceptual framework to gain a deeper understanding of IO's impacts on perceived academic performance.

The last limitation of this study pertains to the sampling method employed. The research utilised convenience sampling, whereby participants were chosen based on their ready availability. As noted by Given (2008), such a sampling method presents challenges in determining whether the findings can be generalised beyond the initial sample or applied to other contexts. Nonetheless, Bryman (2016) argues that convenience sampling is more prevalent and useful than is often acknowledged. In organisational studies, for instance, convenience samples are common and may even surpass the frequency of probability samples. Moreover, Bryman (2016) points out that the extensive preparation required for probability sampling often leads researchers to opt for the more accessible convenience sampling approach despite its limitations.

8.7 Recommendations

Building on the practical implications described above, the following recommendations are proposed to help institutions and educators manage IO and improve digital learning experiences.

8.7.1 Recommendations for Policymakers in Higher Education

Role: Policymakers should establish strategic frameworks and governance structures that minimise IO and ensure sustainable, user-centric digital learning environments.
Recommended Actions:

- Enhance information literacy: Institutions should encourage information literacy workshops to equip students with essential strategies for managing IO and filtering search results efficiently.
- Empower students to fulfill their information needs: Institutions should implement advanced information retrieval systems that incorporate personalised filtering and recommendation mechanisms.

8.7.2 Recommendations for Lecturers in Higher Education

Role: Lecturers play a critical role in structuring digital learning environments to minimise IO and enhance clarity for students.

Recommended Actions:

1. **Address Diverse Information Needs**
   - Provide a variety of supplementary materials to accommodate different learning preferences.
   - Clearly indicate the priority level of each resource using visual cues such as:
     - Prioritised lists (e.g., "Essential," "Recommended," "Optional").
     - Colour coding or symbols (e.g., asterisks for core readings).
2. **Improve Online Discussion Navigation**
   - Set clear participation guidelines for students to maintain relevance and reduce redundant posts.
   - Summarise and interweave key points periodically to maintain coherence and help students follow the discussion flow.
   - Reorient off-topic discussions promptly to the main subject to avoid cognitive drift.
   - Provide immediate guidance to students who appear confused or disengaged, ensuring they can re-engage effectively (Chen, 2003).
3. **Structure Digital Content for Cognitive Efficiency**
   - Break down complex topics into manageable segments and release them progressively (progressive disclosure).
   - Use consistent formatting and labelling across all course materials to reduce cognitive load.

- Avoid duplicating information across multiple platforms unless necessary; instead, centralise key resources in one location (e.g., LMS dashboard).

4. **Support Digital Well-being**

   - Encourage students to adopt time management strategies (e.g., scheduled check-ins for forums and emails).
   - Limit unnecessary notifications by configuring LMS and communication tools to send essential alerts only.
   - Promote healthy digital habits, such as taking breaks during extended online sessions.

8.7.3 Recommendations for Multi-Stakeholder Engagement

Effectively addressing information overload requires a coordinated, multi-stakeholder approach. While policymakers and lecturers play a central role, other groups—such as educational technologists, information literacy champions, library staff, and students—are equally critical in designing and implementing interventions. Their contributions are outlined below.

1. Educational Technologists

Role: Design and maintain digital learning platforms that minimise cognitive load and support intuitive navigation.

Recommended Actions:

- Apply user experience design principles to create intuitive, accessible, and user-friendly interfaces that minimise cognitive effort. For example, implement progressive disclosure techniques to present information in manageable layers, reducing initial complexity and preventing overload.

- Implement personalised dashboards that prioritise essential information and reduce clutter. Develop dashboards that consolidate essential information in a clear and visually structured format.

- Integrate adaptive recommender systems to filter irrelevant content and highlight priority resources.

2. Information Literacy

Role: Promote and deliver training programs that enhance students' ability to manage and evaluate digital information effectively.

Recommended Actions:

- Organise information literacy workshops focusing on filtering, prioritising, and evaluating digital content.
- Provide guidelines for effective search strategies and critical evaluation of online resources.
- Develop self-paced online modules on coping strategies for information overload.
- Collaborate with lecturers to embed information literacy components into course curricula.
- Offer one-to-one consultations for students experiencing overload.

3. Library Staff

Role: Curate and manage academic resources to reduce redundancy and improve relevance for students.

Recommended Actions:

- Create curated reading lists aligned with course objectives to reduce unnecessary information exposure.
- Offer consultation services to help students identify high-quality, relevant resources.
- Implement metadata tagging and categorisation for easier resource discovery.
- Provide alerts for essential updates only, avoiding excessive notifications.

4. Students

Role: Adopt personal coping strategies to manage information flow and reduce cognitive strain.

Recommended Actions:

- Engage in feedback sessions to ensure tools and policies meet real needs.
- Use filtering techniques (e.g., prioritising notifications, unsubscribing from non-essential channels).
- Apply selective attention strategies, focusing on core learning materials first.
- Schedule dedicated time slots for checking messages and updates to avoid constant interruptions.
- Practise digital well-being habits, such as taking breaks and limiting multitasking.

Engaging these stakeholders enables institutions to implement an integrated, multi-level strategy that aligns technological, pedagogical, and behavioural measures to mitigate information overload effectively.

8.8 Directions for Future Research

This study examined the consequences of IO on digital fatigue and perceived performance. Other negative outcomes of IO on learning outcomes and student well-being should be explored in future research; for example, the influence of IO on student satisfaction and discontinuous usage behaviour with digital platforms.

The variance of perceived academic performance explained by digital fatigue is 22%, indicating that future research can address other contributing factors.

Further research should examine how the unique characteristics of various digital platforms influence the experience of IO. For instance, platforms centred on video content—like YouTube—may trigger different overload patterns compared to text-centric platforms such as X, where message length is limited. Moreover, existing literature suggests that the cognitive processing required for video content differs from that needed for text (Schluer).

Future research should address the limitations of this study's cross-sectional design, which examines students' use of DLTs at a single point in time. This approach restricts the ability to establish causal relationships within the conceptual framework, as usage behaviour is continuously shaped by cognitive abilities and environmental demands (Shi et al., 2020). For instance, poor academic performance may lead students to either limit their engagement with DLTs due to frustration or increase their usage in an effort to compensate. To better understand these dynamic interactions, future studies should adopt a longitudinal research design that tracks changes in behaviour over time.

Future research could explore the potential of AI-powered solutions—such as automated summarisation, intelligent content curation, and personalised learning pathways—to alleviate information overload in digital learning environments. A key research question is: *To what extent can generative AI effectively reduce cognitive load for students, and what pedagogical frameworks ensure its optimal integration into digital learning tools?* Such studies should also examine the ethical and practical implications of embedding AI-driven features in educational platforms, including transparency, fairness, and learner autonomy.

While this thesis primarily examined IO in the context of learning, the digital environment also imposes significant cognitive demands related to security and privacy. These demands can be conceptualised as a distinct form of IO, warranting further investigation. Future research should explore privacy fatigue as a manifestation of system features overload. Students are frequently required to manage privacy settings, consent to cookie policies, and navigate complex terms of service—tasks that are repetitive and cognitively demanding. Understanding how these activities contribute to digital fatigue and whether they increase susceptibility to risky online behaviours represents an important research avenue.

Future research should investigate how recent transformations in social media platforms—such as X (formerly Twitter) under Elon Musk and the rise of alternative platforms—affect information overload in educational contexts. Key questions include whether algorithm-driven feeds amplify content overload compared to chronological models and how platform fragmentation (e.g., using X, Discord, TikTok for academic purposes) contributes to system features overload and digital fatigue.

8.9 Thesis Conclusion

This study set out to investigate the phenomenon of IO induced by DLTs and its subsequent effects on digital fatigue and perceived academic performance among higher education students in the UK. Through a mixed-methods approach involving a conceptual framework development, quantitative testing with undergraduate participants, and a qualitative systematic review, the research provided a multifaceted exploration of IO. The initial phase of this research involved developing a conceptual framework, which identified four distinct dimensions of IO: content, communication, social, and system feature overload. This framework not only clarifies the diverse triggers associated with DLTs—such as information volume, system complexity, hyperconnectivity, and engagement demands—but also establishes the link between these overload types and the onset of digital fatigue. This theoretical foundation enabled the formulation of specific hypotheses regarding how different overload dimensions impair students' ability to concentrate and retain information, ultimately affecting their perceived academic performance.

In the second phase, quantitative analysis using an online questionnaire with 200 UK undergraduate students empirically tested these hypotheses. The findings confirmed that excessive use of digital learning platforms leads to significant cognitive strain and digital fatigue. This fatigue, in turn, has a measurable negative impact on students perceived academic performance, underscoring the importance of managing IO in digital environments. This study employed PLS-SEM using R as its primary analytical framework, enabling a rigorous examination of the theoretical model and providing robust insights into complex interrelationships.

The third phase, a systematic review of 38 articles analysed through directed thematic analysis, identified a range of strategies for mitigating IO. These strategies were grouped into four primary themes: personal strategies, organisational and technological solutions, educational and training approaches, and improved communication and information sharing. The review highlights the critical role of information literacy workshops, advanced information retrieval systems, and structured digital content management in reducing overload and supporting student well-being. Many lecturers already adopt effective course-design practices (clear structure, consistent labelling), and COVID-era adaptations demonstrated how coordinated institutional action (streamlined communications, consolidated calendars, and structured course design) can materially reduce student confusion and IO. Translating these measures into practice requires pairing implementation with simple, rapid evaluation (student surveys of perceived overload, LMS access analytics, and small-scale pilot tests) so interventions can be iteratively refined and scaled based on evidence.

In terms of practical implications, the study emphasises that IO is a tangible issue that adversely affects both student well-being and academic outcomes. Higher education institutions must acknowledge this challenge and implement proactive strategies to alleviate cognitive strain, thereby enhancing both student engagement and retention. The versatile conceptual framework developed as a result of this original analysis can serve as a valuable tool for institutions to diagnose overload issues and design targeted interventions.

Despite its contributions, this research has limitations, including its focus on UK-based higher education contexts and the use of cross-sectional data; future work should validate the framework across diverse educational systems, adopt longitudinal or experimental designs to establish causal dynamics, and examine emerging solutions (for example, AI-mediated summarisation and privacy-aware personalisation).

In summary, this thesis advances theoretical clarity and supplies actionable guidance for multi-stakeholder responses — enabling institutions, course teams, and educational technologists to diagnose overload better and to design evidence-informed interventions that protect student well-being and support academic success in increasingly digital learning environments.

Publications

1. *Reconceptualising the Multifaceted Nature of Information Overload in Digital Learning Environments*
   *Status:*Ready to submit to Journal of Trends in Cognitive Sciences
2. *Information Overload as a Multifaceted Perspective in the Context of Digital Learning Tools: An Empirical Study*
   Status: Ready to submit to Jouranl Information Processing & Management
3. *Strategies for Managing Information Overload: A Systematic Review*
   Status: submitted to Journal of Documentation.

Reflections on the PhD Journey

Pursuing this doctoral research has been an intellectually demanding and personally transformative journey. The project began from a clear motivation to understand the growing problem of information overload in higher education digital learning environments; this motivation framed the research questions and helped sustain me through the more difficult phases of the work. The research aim, to reconceptualise information overload as a multifaceted phenomenon within digital learning tools, provided a steady anchor for the project and guided methodological choices throughout.

Choosing and implementing a mixed-methods design was one of the most important methodological decisions I made. Combining a quantitative online survey to test the conceptual framework, with a qualitative systematic review allowed me to both test hypotheses and generate practical strategies — an approach that suited the complexity of the phenomenon under study. Designing the questionnaire, piloting it, and then applying PLS-SEM analysis taught me valuable lessons in instrument development, construct operationalisation and the interpretation of structural models. The systematic review phase, meanwhile, sharpened my abilities in systematic search strategies, thematic coding and synthesis of diverse evidence. The methodological chapters document these processes and the justifications for them.

Throughout the work I developed a deeper theoretical appreciation for how stress theory and person–environment fit can be integrated to explain the pathway from digital learning tool characteristics to overload and digital fatigue. Empirically, I was surprised to find that content overload emerged as the strongest predictor of digital fatigue and that technology self-efficacy sometimes amplified, rather than attenuated, the effects of content overload. These findings forced me to reconsider some of my initial expectations and helped refine the thesis's theoretical contributions. The experience of revising hypotheses in light of unexpected data strengthened my capacity for critical reflection and empirical humility.

Practical and professional development Beyond theory and methods, the PhD process has substantially expanded my professional skills. I learned to manage a multi-stage research project, work with survey platforms and statistical software (including R and smartPLS), and execute a rigorous systematic review. I also developed communication skills through writing for varied audiences (thesis chapters, possible journal manuscripts) and learned how to structure arguments for clarity and scholarly impact. The ethical and data-management practices adopted during the study (including gaining departmental ethics approval and GDPR-compliant data handling) reinforced my commitment to responsible research conduct.

The project posed several practical challenges: recruiting a sufficiently large, complete survey sample; ensuring measurement validity in a complex theoretical model; and balancing depth of literature coverage with feasibility in the systematic review. I addressed these by careful piloting, iterative instrument refinement, close supervision and adopting a transparent coding and synthesis protocol for the review. Time management and sustaining momentum were recurring personal challenges; scheduling, breaking tasks into small objectives, and regular meetings with my supervisors helped maintain progress. I remain grateful for the guidance and support received during difficult moments.

This thesis contributes both conceptual clarity (a multidimensional conceptualisation of information overload) and practical guidance (synthesised strategies to mitigate overload). Importantly, the study highlights that effective responses require coordinated action across technologists, librarians, lecturers and students — an insight I plan to explore further in post-doctoral work on AI-mediated summarisation and privacy-aware personalisation. The Directions for Future Research section summarises concrete next steps that build directly on the thesis findings.

Completing this PhD has been an exercise in persistence, openness to critique and continual learning. The academic gains are accompanied by deep personal growth: greater resilience, improved project management, and a clearer sense of the research agenda I wish to pursue next. I am indebted to my supervisors, colleagues, family and friends for their encouragement and practical support.

Appendix A

Appendix A: Survey Questions

Appendix A presents the complete online survey questionnaire instrument administered to participants for the quantitative phase of this study (Phase 3). It includes the participant consent form, demographic questions, and all items used to measure the core constructs of the research.

Consent Form

Thank you for agreeing to take part in this survey.

Name of department: Department of Computer and Information Sciences.

Title of the study: Understanding the Influence of Digital Learning Environments Experience on Higher Education Students' Performance.

Introduction

You are being invited to participate in a study run by Salah Kashlot, PhD student from the Department of Computer and Information Sciences at the University of Strathclyde, to understand the perceptions of students regarding the use of Digital Learning Tools. Digital learning tools are any technological resources, applications, or platforms that students use to enhance their learning in a digital environment. They include both officially recommended tools endorsed by educational institutions as well as any other digital tools that students choose to incorporate into their learning process such as (learning management systems social networking services, online forums, instant messaging apps, and various other digital platforms).

What is the purpose of this research?

This study aims to investigate particular aspects of digital learning tools that could be linked to types of information overload among students in higher education institutions in the UK.

Do you have to take part?

The study targets higher education students in the UK. Participating in this study does not involve any known risks, as it will be carried out exclusively online and they are under no obligation to participate in the questionnaire; it is entirely voluntary. You have the freedom to discontinue their participation or withdraw from the questionnaire at any point without facing any consequences.

What data will be collected / How these will be used and managed

- Data collected during this study will not include personally identifiable or sensitive information.
- Rest assured that all information gathered will be treated with the utmost confidentiality and used solely for the purpose of this research project.
- Reports generated from this data will be employed for the final thesis and may potentially be published in scientific journals.
- All data gathered will be treated with the UK Data Protection Act and the General Data Protection Regulation, will be held securely in store on the university's secure OneDrive server, after which they will be deleted upon completion of the researcher's PhD.

Estimated survey completion time: 7 mins.

If you have any questions or concerns about this survey or the research, please do not hesitate please contact me, my supervisors, or the department using the details below:

Researcher

Salah Kashlot, PhD Student email: salah.kashlot@strath.ac.uk

Supervisors

1. Dr. Yashar Moshfeghi - email: yashar.moshfeghi@strath.ac.uk
2. Prof. Ian Ruthven - email: ian.ruthven@strath.ac.uk

Department of Computer and Information Sciences

University of Strathclyde

Livingstone Tower, 26 Richmond Street, Glasgow G1 1XH, Scotland, UK

Departmental Contact- email: ethics@cis.strath.ac.uk

Telephone: 01415482952

Consent Form

By proceeding with this questionnaire, you acknowledge and affirm the following:

- I confirm that I have read and understood the Participant Information Sheet for the above project and the researcher has answered any queries to my satisfaction.
- I confirm that you are at least 18 years old.
- Your participation in this study is voluntary, free to withdraw from the survey at any time, up to the point of completion.
- I consent to being a participant in the project.
- I understand that anonymised data (i.e. data that do not identify me personally) cannot be withdrawn once they have been included in the study.
- I understand that I can request the withdrawal from the study of some personal information and that whenever possible researchers will comply with my request.

○ **Yes, I consent**

○ **No, I do not consent**

Thank you for agreeing to take part in this survey.

Name of department: Department of Computer and Information Sciences.

Title of the study: Understanding the Influence of Digital Learning Environments Experience on Higher Education Students' Performance.

Introduction

You are being invited to participate in a study run by Salah Kashlot, PhD student from the Department of Computer and Information Sciences at the University of Strathclyde, to understand the perceptions of students regarding the use of Digital Learning Tools. Digital learning tools are any technological resources, applications, or platforms that students use to enhance their learning in a digital environment. They include both officially recommended tools endorsed by educational institutions as well as any other digital tools that students choose to incorporate into their learning process such as (learning management systems social networking services, online forums, instant messaging apps, and various other digital platforms).

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What data will be collected / How these will be used and managed

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Researcher

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Consent Form

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- I understand that I can request the withdrawal from the study of some personal information and that whenever possible researchers will comply with my request.

○ **Yes, I consent**

○ **No, I do not consent**

Demographic

What is your age (in years)?

What best describes your gender identity?

- Male
- Female
- Please describe your gender if you prefer another term.

Which is a general area of your study?

- Science
- Engineering
- Humanities and Social Sciences
- Business

What is your current academic year?

- 1st year
- 2nd year
- J3rd year
- 4th year
- Other

Information Characteristics

I would like your opinions on the information you receive through digital learning tools, please click the frequency that best matches your opinion.

	Never	Rarely	Sometimes	Often	Always
1.I feel overwhelmed by the quantity of information that I receive through digital learning tools (i.e., recorded videos, emails, digital attachments, social networking sites, online forums, etc.)					
2.I feel it is easy to navigate the information provided by digital learning tools in my daily learning activities.					
3.I feel stressed by the quantity of information I receive through my digital learning tools.					
4.I feel that the information provided by digital learning tools is useless to my course.					

	Never	Rarely	Sometimes	Often	Always
5.I feel that the information from digital learning tools is not related to the topics I'm studying.	○	○	○	○	○
6.I feel I waste time having to filter information on digital learning tools.	○	○	○	○	○
7.I feel the information in digital learning tools can be ambiguous.	○	○	○	○	○
8.I feel useful to receive the same information in different formats,	○	○	○	○	○
9.I feel that information in digital learning tools can mean different things to different students.	○	○	○	○	○

Communication characteristics

I would like your opinions on the extent of your connectedness with digital learning tools, please click the frequency that best matches your opinion.

	Never	Rarely	Sometimes	Often	Always
1.I feel it is easy to stay constantly connected to digital learning tools.	○	○	○	○	○
2.I feel immersed in digital learning tools.	○	○	○	○	○
3.I feel easily reachable by instructors (or peers) through various digital learning tools	○	○	○	○	○
4.I receive unscheduled interruptions during my study routine.	○	○	○	○	○
5.I am not forced to pause my current activity due to demands initiated by digital learning tools.	○	○	○	○	○
6.I feel stressed due to interruptions from digital learning tools.	○	○	○	○	○

Engagement Characterises

I would like your opinions on the extent of your engagement with digital learning tools, please click the frequency that best matches your opinion.

	Never	Rarely	Sometimes	Often	Always
1.I feel overwhelmed with the level of interaction required by digital learning tools.	○	○	○	○	○
2.I feel that interacting with digital learning tools to manage my tasks is not challenging.	○	○	○	○	○
3.I feel stressed by the level of interaction required through digital learning tools.	○	○	○	○	○

Dynamic Characteristics

I would like your opinions on your dynamic of digital learning tools, please click the frequency that best matches your opinion.

	Never	Rarely	Sometimes	Often	Always
1. I feel that there are changes in the features of digital learning tools.	○	○	○	○	○
2.I feel that interfaces of digital learning tools change.	○	○	○	○	○

	Never	Rarely	Sometimes	Often	Always
3. I feel that digital learning tools demand continuous adaptation due to rapid software changes.	O	O	O	O	O
4.I feel that the functions of digital learning tools are easy to use.	O	O	O	O	O
5.I feel that learning to use digital learning tools is not easy for me.	O	O	O	O	O
6.I feel that digital learning tools make it difficult to achieve my desired learning outcomes.	O	O	O	O	O

Overload

I would like your opinions on the extent of your suffering from overload induced by digital learning tools, please click the frequency that best matches your opinion.

	Never	Rarely	Sometimes	Often	Always
1. I feel distracted by content in digital learning tools.	O	O	O	O	O
2. I feel that the content of digital learning tools is within my capacity to process.	O	O	O	O	O
3. I feel overloaded with content from digital learning tools.	O	O	O	O	O
4. I feel I receive too much communication from instructors (or peers) through digital learning tools.	O	O	O	O	O
5. I feel it is challenging to handle communications through digital learning tools.	O	O	O	O	O
6. I feel overwhelmed by the volume of communication through digital learning tools.	O	O	O	O	O
7.I feel that I am highly involved in my peers' social interactions through digital learning tools.	O	O	O	O	O
8. I do not feel stressed by social interactions through digital learning tools.	O	O	O	O	O
9. I feel irritated, because I paying too much attention to posts of peers within digital.	O	O	O	O	O
10. I feel that digital learning tools distract me with unnecessary features.	O	O	O	O	O
11. I feel that tools with too many features of digital learning tools hinder my productivity.	O	O	O	O	O
12. I feel that tools with too many features in digital learning tools overload me.	O	O	O	O	O

Fatigue

I would like your opinions on your perceived level of tiredness induced by digital learning tools, please click the frequency that best matches your opinion.

	Never	Rarely	Sometimes	Often	Always
1. I feel drained when using digital learning tools.	O	O	O	O	O
2. I feel that it is easy to relax after using digital learning tools.	O	O	O	O	O
3. 1. After a session of using digital learning tools, I feel exhausted.	O	O	O	O	O

Performance

I would like your opinions on your perceived level of academic performance, please click the frequency that best matches your opinion.

	Never	Rarely	Sometimes	Often	Always
1. I feel capable of conducting my academic tasks.	O	O	O	O	O
2. I feel that I struggle to conduct my course assignments.	O	O	O	O	O
3. I feel that I have learned how to successfully perform my coursework in an efficient manner.	O	O	O	O	O
4. I feel that I have performed academically as well as I anticipated I would.	O	O	O	O	O

Technology self-efficacy

I would like your opinions on your self-efficacy to be able to use the new technology, please click the frequency that best matches your opinion.

I feel able to use the new technology:

	Never	Rarely	Sometimes	Often	Always
.... if there is no one around to tell me what to do;	O	O	O	O	O
.. if I had just the built-in help/guide facility for assistance;	O	O	O	O	O
... if I had never used a technology like this before.	O	O	O	O	O

Block 10

Powered by Qualtrics

Appendix B

Appendix B: Ethical Approval

This appendix (Appendix B) contains the formal ethical approval documentation for this research, as granted by the Department of Computer and Information Sciences Ethics Committee at the University of Strathclyde (Application ID: 2425).

CIS Ethics Approval

Title of research:

Understanding the Influence of Digital Learning Environments Experience on Higher Education Students' Performance.

Summary of research (short overview of the background and aims of this study):

Blended learning environments frequently give rise to stressful circumstances among students. Without a doubt, students within today's digital educational environment are exposed to substantial volumes of information from a diverse range of sources, primarily through Digital Learning Tools (DLTs). Contemporary trends toward digitalization only exacerbate this challenge. The use of digital learning tools results in the generation of a vast volume of information that surpasses students' capacity to manage effectively. This, as a result, generates a phenomenon called in information overload. In this study, we suggest the manifestations of information overload, encompassing content overload, communication overload, social overload, and system features overload, are more typical in the context of Digital Learning Tools.

In this survey, Digital Learning Tools encompass a wide array of technological resources, applications, and platforms that students employ to enrich their learning and educational experiences within a digital environment. These tools utilize digital technologies to provide diverse and innovative means for students to access educational content, interact with course materials, collaborate with peers, and engage with instructors and learning resources. They include both officially recommended tools endorsed by educational institutions, such as learning management systems, as well as any other digital tools that students choose to incorporate into their learning process. These may encompass personal devices, third-party applications, social networking services, online forums which can be either officially designated by the institution or independently created by students, instant messaging apps, and various other digital platforms.

How will participants be recruited?

This study engages participants recruited via the Prolific website, known for its credibility in research participant recruitment. Prolific guarantees voluntary and fair compensation for participants' contributions.

Participant eligibility for the sample is determined using Prolific's prescreeners, ensuring access exclusively for eligible individuals. To achieve a diverse and representative sample of the population, participants must satisfy specific criteria outlined in the prescreening process:

Age: Participants must be 18 years or older.

Country of Residence: Participants must currently reside in the United Kingdom.

Student Status: Participants must be enrolled as undergraduate students.

Year of Study: Participants should be in their 1st, 2nd, 3rd, or 4th year of undergraduate studies.

Prolific manages this prescreening process by using its platform to filter and verify participants based on the established criteria. The system restricts access to the survey only to individuals meeting these eligibility requirements, ensuring that the sample collected remains in line with the specified criteria throughout the data collection process.

What will the participants be told about the proposed research study? Either upload or include a copy of the briefing notes issued to participants. In particular this should include details of yourself, the context of the study and an overview of the data that you plan to collect, your supervisor, and contact details for the Departmental Ethics Committee.

I will distribute the Participant Information Sheet (PIS) to all prospective participants, allowing them to review the research details before initiating the online survey. Consent will be obtained at the beginning of the survey when participants click the 'Yes, I consent' button to start the survey, and prior to submitting their responses.

See Participant Information Sheet (PIS)

How will consent be demonstrated? Either upload or include here a copy of the consent form/instructions issued to participants. It is particularly important that you make the rights of the participants to freely withdraw from the study at any point (if they begin to feel stressed for example), nor feel under any pressure or obligation to complete the study, answer any particular question, or undertake any particular task. Their rights regarding associated data collected should also be made explicit.

Consent will be obtained at the start of the online survey by clicking the Yes, I consent" button to start the survey. and prior to submission:

Affirmation and Consent:

By proceeding with this questionnaire, you acknowledge and affirm the following:

• I confirm that I have read and understood the Participant Information Sheet for the above

project and the researcher has answered any queries to my satisfaction.

• I confirm that you are at least 18 years old.

• Your participation in this study is voluntary, free to withdraw from the survey at any time,

up to the point of completion.

• I consent to being a participant in the project.

• I understand that anonymised data (i.e. data that do not identify me personally) cannot be

withdrawn once they have been included in the study.

• I understand that I can request the withdrawal from the study of some personal.

information and that whenever possible researchers will comply with my request.

See Participant Information Sheet (PIS)

What will participants be expected to do? Either upload or include a copy of the instructions issued to participants along with a copy of or link to the survey, interview

script or task description you intend to carry out. Please also confirm (where appropriate) that your supervisor has seen and approved both your planned study, and this associated ethics application.

The survey can be previewed:

https://strathsci.qualtrics.com/jfe/form/SV_8Gj43MuLEi8aEpE

I have sent the plan of the study and the ethics application to my supervisors Dr. Yashar, Prof.Ian and they have seen and approved them.

What data will be collected and how will it be captured and stored? In particular indicate how adherence to the Data Protection Act and the General Data Protection Regulation (GDPR) will be guaranteed and how participant confidentiality will be handled.

The data collection process for this study will adhere to the following guidelines:

• No personally identifiable information or sensitive data will be gathered during this study.

• Any reports resulting from the collected data will be utilized for the final thesis and may be published in scientific journals.

• Any identifiable data will be removed from the dataset in strict compliance with the UK Data Protection Act and the General Data Protection Regulation.

• All collected information will be held in strict confidence and utilized exclusively for the research project, as mandated by the requirements for a PhD from the Department of Computer and Information Sciences at Strathclyde University.

• All information and data collected during the survey will be deleted after I finish my PhD study and any publications related to the project.

See Participant Information Sheet (PIS)

How will the data be processed? (e.g. analysed, reported, visualised, integrated with other data, etc.) Please pay particular attention to describe how personal or sensitive data will be handled and how GDPR regulations will be met.

I intend to utilize the survey data collected through Qualtrics for both my PhD thesis and a journal article. The data analysis will be conducted using applications such as SPSS, and smartPLS. To ensure data security, all information will be stored on the university's secure OneDrive server. Access to the data will be restricted to myself and my supervisor, maintaining confidentiality and data protection throughout the research process.

How and when will data be disposed of? Either upload a copy of your data management plan or describe how data will be disposed.

The data will be retained until it is no longer required for the study, specifically until the completion of my PhD thesis. Upon successfully passing my thesis, the data will be securely and permanently destroyed.

Appendix C

Appendix C: Participant Information Sheet

Appendix C contains the Participant Information Sheet (PIS) that was provided to all potential participants prior to enrolling in the online survey

Participant information sheet

Name of department: Department of Computer and Information Sciences.
Title of the study: Understanding the Influence of Digital Learning Environments Experience on Higher Education Students' Performance.

Introduction
You are being invited to participate in a study run by Salah Kashlot, PhD student from the Department of Computer and Information Sciences at the University of Strathclyde, to understand the perceptions of students regarding the use of Digital Learning Tools. Digital learning tools are any technological resources, applications, or platforms that students use to enhance their learning in a digital environment. They include both officially recommended tools endorsed by educational institutions as well as any other digital tools that students choose to incorporate into their learning process such as (learning management systems social networking services, online forums, instant messaging apps, and various other digital platforms).

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Do you have to take part?
The study targets higher education students in the UK. Participating in this study does not involve any known risks, as it will be carried out exclusively online and they are under no obligation to participate in the questionnaire; it is entirely voluntary. You have the freedom to discontinue their participation or withdraw from the questionnaire at any point without facing any consequences.

What data will be collected / How these will be used and managed

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- Rest assured that all information gathered will be treated with the utmost confidentiality and used solely for the purpose of this research project.
- Reports generated from this data will be employed for the final thesis and may potentially be published in scientific journals.
- All data gathered will be treated with the UK Data Protection Act and the General Data Protection Regulation, will be held securely in store on the university's secure OneDrive server, after which they will be deleted upon completion of the researcher's PhD.

Estimated survey completion time: 15.

If you have any questions or concerns about this survey or the research, please do not hesitate please contact me, my supervisors, or the department using the details below:

Researcher
Salah Kashlot, PhD Student email: salah.kashlot@strath.ac.uk
Supervisors
1. Dr. Yashar Moshfeghi - email: yashar.moshfeghi@strath.ac.uk
2. Prof. Ian Ruthven - email: ian.ruthven@strath.ac.uk
Department of Computer and Information Sciences
University of Strathclyde
Livingstone Tower, 26 Richmond Street, Glasgow G1 1XH, Scotland, UK
Departmental Contact- email: ethics@cis.strath.ac.uk
Telephone: 01415482952

Appendix D

Appendix D: PLS Bootstrapping Paths

Appendix D presents the visual output (Figure 8.1) derived from the PLS-SEM bootstrapping analysis performed in RStudio, illustrating the estimated structural model paths and their significance levels as discussed in Chapter 5.

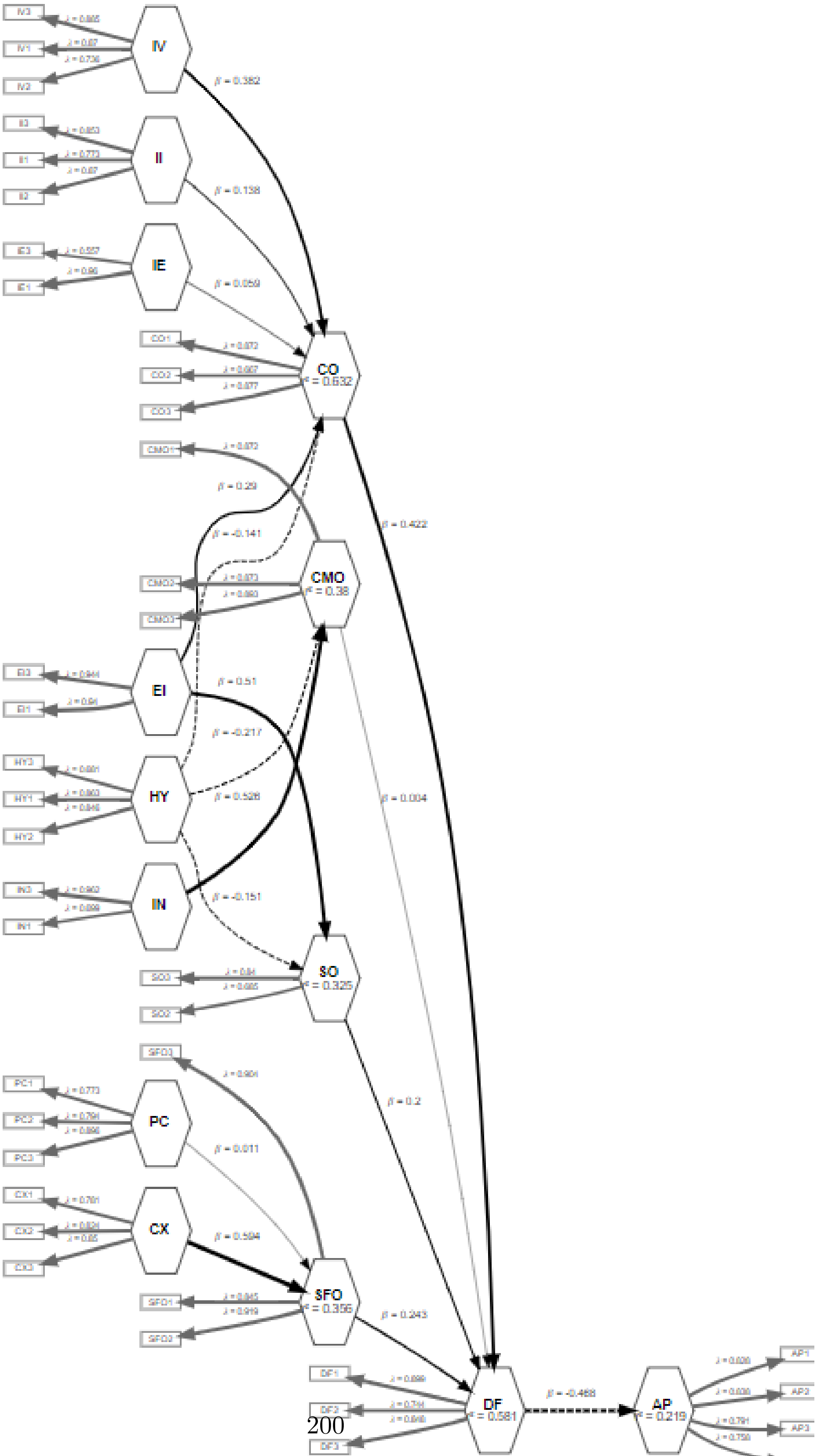
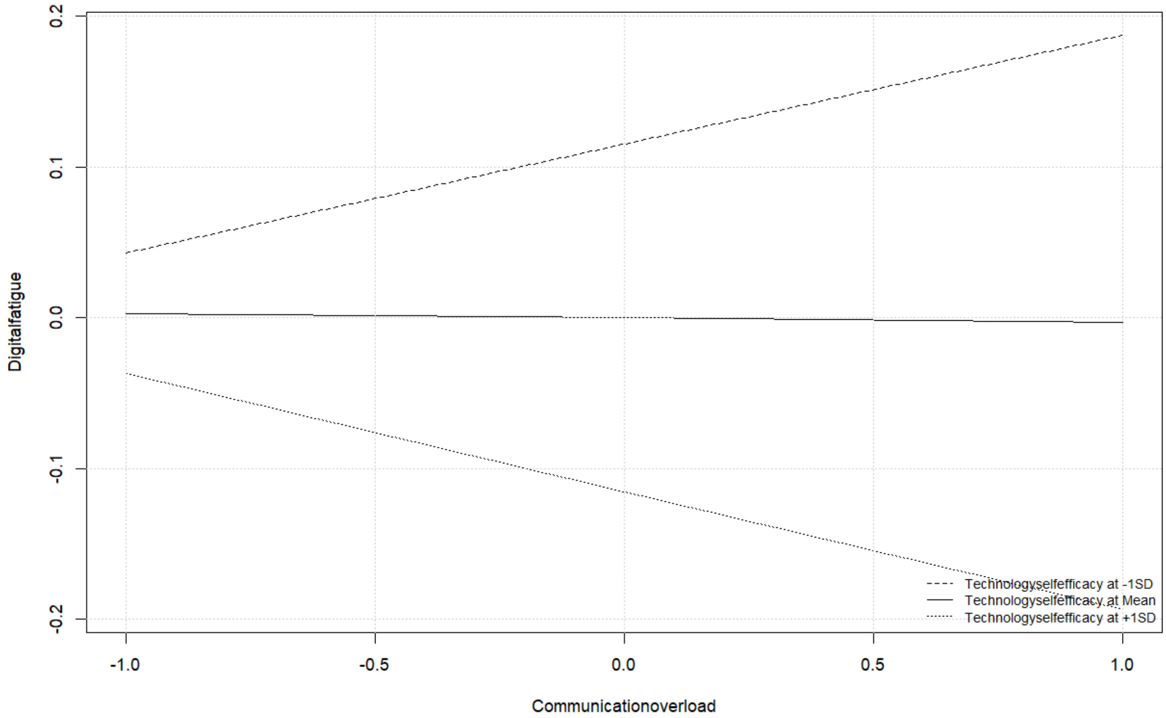


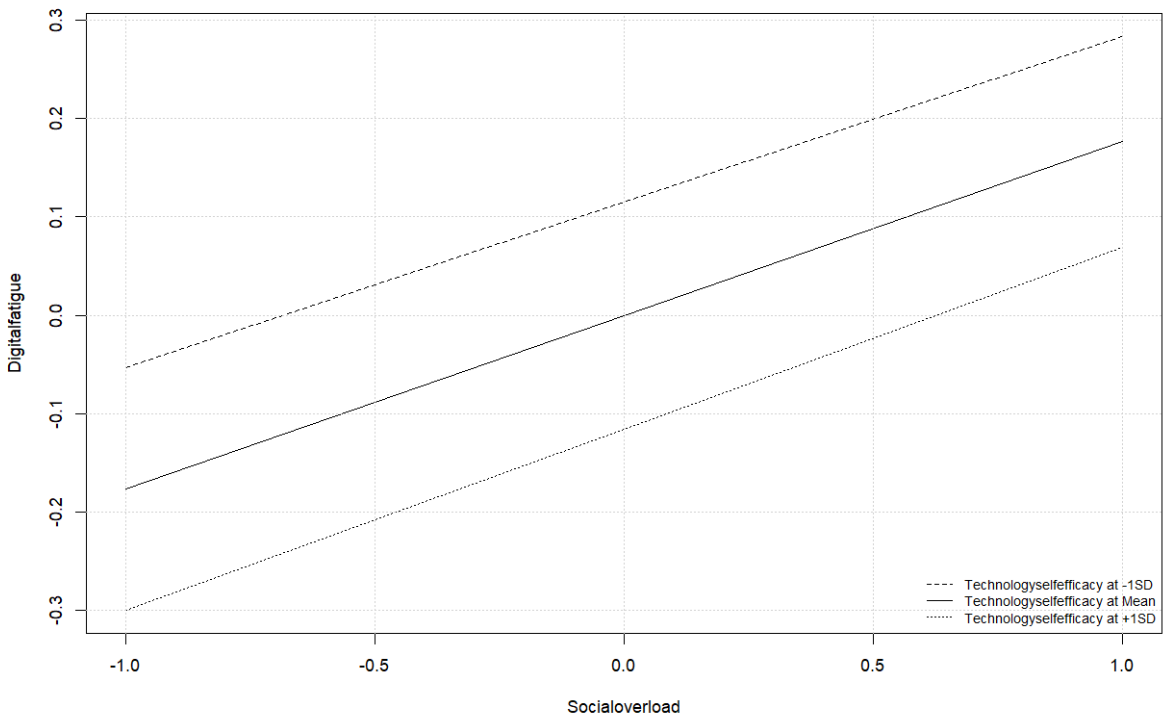
Figure D.1: PLS bootstrapping paths (screenshot from RStudio)

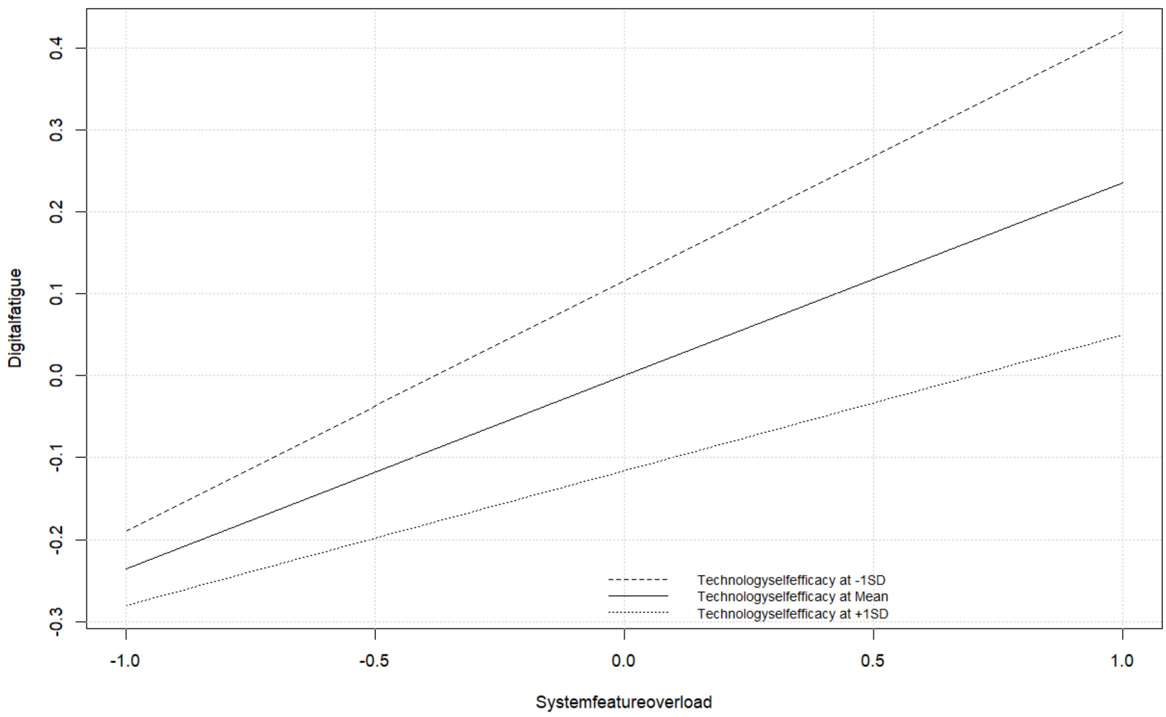
Appendix E

Appendix E: Plots Moderation

This appendix (Appendix E) contains the plots generated for the moderation analysis detailed in Chapter 5 (Section 5.5). These graphs visually represent the tested interaction effects.


Digitalfatigue
Communicationoverload
Technologyselfefficacy at -1SD
Technologyselfefficacy at Mean
Technologyselfefficacy at +1SD


Digitalfatigue
Socialoverload
Technologyselfefficacy at -1SD
Technologyselfefficacy at Mean
Technologyselfefficacy at +1SD



Digitalfatigue
0.4
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
Technologyselfefficacy at -1SD
Technologyselfefficacy at Mean
Technologyselfefficacy at +1SD
-1.0
-0.5
0.0
0.5
1.0
Systemfeatureoverload

Appendix F

Appendix F: Results UsingR

This appendix (Appendix F) presents detailed output tables and results generated using R (SEMinR package) for the PLS-SEM analysis discussed in Chapter 5. It includes supplementary figures displaying key statistical outputs such as outer loadings, discriminant validity checks (Fornell-Larcker criterion), R-squared values, VIF values for collinearity assessment, path coefficient estimations, and total effect

Outer loading. (Source: au screenshot from RStudio)

```
R 4.3.2 · ~/PLS Smart/Structural Equation Modeling/R/Information overlaod/final Results/
> # Inspect the indicator loadings
> summary_corp$loadings
         IV     II     IE     HY     EI     IN     PC     CX     CO    CMO     SO    SFO     DF     AP
IV1   0.870  0.000  0.000 -0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000 -0.000
IV2   0.736  0.000  0.000 -0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000 -0.000
IV3   0.885  0.000  0.000 -0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000 -0.000
II1   0.000  0.773  0.000 -0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000 -0.000
II2   0.000  0.870  0.000 -0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000 -0.000
II3   0.000  0.853  0.000 -0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000 -0.000
IE1   0.000  0.000  0.960 -0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000 -0.000
IE3   0.000  0.000  0.557 -0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000 -0.000
HY1  -0.000 -0.000 -0.000  0.863 -0.000 -0.000  0.000 -0.000 -0.000 -0.000 -0.000 -0.000 -0.000  0.000
HY2  -0.000 -0.000 -0.000  0.846 -0.000 -0.000  0.000 -0.000 -0.000 -0.000 -0.000 -0.000 -0.000  0.000
HY3  -0.000 -0.000 -0.000  0.681 -0.000 -0.000  0.000 -0.000 -0.000 -0.000 -0.000 -0.000 -0.000  0.000
IN1   0.000  0.000  0.000 -0.000  0.000  0.699  0.000  0.000  0.000  0.000  0.000  0.000  0.000 -0.000
IN3   0.000  0.000  0.000 -0.000  0.000  0.962  0.000  0.000  0.000  0.000  0.000  0.000  0.000 -0.000
EI1   0.000  0.000  0.000 -0.000  0.940  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000 -0.000
EI3   0.000  0.000  0.000 -0.000  0.944  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000 -0.000
PC1   0.000  0.000  0.000  0.000  0.000  0.000  0.773  0.000  0.000  0.000  0.000  0.000  0.000  0.000
PC2   0.000  0.000  0.000  0.000  0.000  0.000  0.794  0.000  0.000  0.000  0.000  0.000  0.000  0.000
PC3   0.000  0.000  0.000  0.000  0.000  0.000  0.896  0.000  0.000  0.000  0.000  0.000  0.000 -0.000
CX1   0.000  0.000  0.000 -0.000  0.000  0.000  0.000  0.781  0.000  0.000  0.000  0.000  0.000 -0.000
CX2   0.000  0.000  0.000 -0.000  0.000  0.000  0.000  0.824  0.000  0.000  0.000  0.000  0.000 -0.000
CX3   0.000  0.000  0.000 -0.000  0.000  0.000  0.000  0.850  0.000  0.000  0.000  0.000  0.000 -0.000
CO1   0.000  0.000  0.000 -0.000  0.000  0.000  0.000  0.000  0.872  0.000  0.000  0.000  0.000 -0.000
CO2   0.000  0.000  0.000 -0.000  0.000  0.000  0.000  0.000  0.667  0.000  0.000  0.000  0.000 -0.000
CO3   0.000  0.000  0.000 -0.000  0.000  0.000  0.000  0.000  0.877  0.000  0.000  0.000  0.000 -0.000
CMO1  0.000  0.000  0.000 -0.000  0.000  0.000  0.000  0.000  0.000  0.872  0.000  0.000  0.000 -0.000
CMO2  0.000  0.000  0.000 -0.000  0.000  0.000  0.000  0.000  0.000  0.873  0.000  0.000  0.000 -0.000
CMO3  0.000  0.000  0.000 -0.000  0.000  0.000  0.000  0.000  0.000  0.893  0.000  0.000  0.000 -0.000
SO2   0.000  0.000  0.000 -0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.685  0.000  0.000 -0.000
SO3   0.000  0.000  0.000 -0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.840  0.000  0.000 -0.000
SFO1  0.000  0.000  0.000 -0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.845  0.000 -0.000
SFO2  0.000  0.000  0.000 -0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.919  0.000 -0.000
SFO3  0.000  0.000  0.000 -0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.904  0.000 -0.000
DF1   0.000  0.000  0.000 -0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.899 -0.000
DF2   0.000  0.000  0.000 -0.000  0.000  0.000 -0.000  0.000  0.000  0.000  0.000  0.000  0.744 -0.000
DF3   0.000  0.000  0.000 -0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.848 -0.000
AP1  -0.000 -0.000 -0.000  0.000 -0.000 -0.000  0.000 -0.000 -0.000 -0.000 -0.000 -0.000 -0.000  0.828
AP2  -0.000 -0.000 -0.000  0.000 -0.000 -0.000 -0.000 -0.000 -0.000 -0.000 -0.000 -0.000 -0.000  0.838
AP3  -0.000 -0.000 -0.000  0.000 -0.000 -0.000  0.000 -0.000 -0.000 -0.000 -0.000 -0.000 -0.000  0.791
AP4  -0.000 -0.000 -0.000  0.000 -0.000 -0.000  0.000 -0.000 -0.000 -0.000 -0.000 -0.000 -0.000  0.758
```

Fornell-Larker Criterion. (Source: au screenshot from RStudio)

```
R 4.3.2 · ~/PLS Smart/Structural Equation Modeling/R/Information overlaod/final Results/
> # Inspect the Fornell-Larcker criterion
> summary_corp$validity$fl_criteria
         IV     II     IE     HY     EI     IN     PC     CX     CO    CMO     SO    SFO     DF     AP
IV    0.833      .      .      .      .      .      .      .      .      .      .      .      .      .
II    0.518  0.833      .      .      .      .      .      .      .      .      .      .      .      .
IE    0.439  0.703  0.785      .      .      .      .      .      .      .      .      .      .      .
HY   -0.327 -0.366 -0.286  0.801      .      .      .      .      .      .      .      .      .      .
EI    0.650  0.503  0.417 -0.276  0.942      .      .      .      .      .      .      .      .      .
IN    0.515  0.485  0.404 -0.249  0.622  0.841      .      .      .      .      .      .      .      .
PC    0.142  0.198  0.219  0.131  0.268  0.261  0.823      .      .      .      .      .      .      .
CX    0.578  0.547  0.442 -0.449  0.676  0.535  0.213  0.819      .      .      .      .      .      .
CO    0.713  0.574  0.485 -0.413  0.671  0.553  0.127  0.696  0.811      .      .      .      .      .
CMO   0.601  0.537  0.465 -0.348  0.679  0.580  0.194  0.672  0.717  0.879      .      .      .      .
SO    0.548  0.397  0.393 -0.291  0.552  0.599  0.122  0.520  0.562  0.638  0.766      .      .      .
SFO   0.640  0.553  0.509 -0.437  0.572  0.567  0.138  0.597  0.716  0.667  0.581  0.890      .      .
DF    0.584  0.555  0.436 -0.483  0.626  0.560  0.116  0.655  0.712  0.597  0.581  0.665  0.833      .
AP   -0.473 -0.420 -0.349  0.276 -0.425 -0.270  0.013 -0.489 -0.518 -0.412 -0.387 -0.454 -0.468  0.805

FL Criteria table reports square root of AVE on the diagonal and construct correlations on the lower triangle.
>
```

R2, and adjusted R2 values. (Source: au screenshot from RStudio)

```
R 4.3.2 · ~/PLS Smart/Structural Equation Modeling/R/Information overlaod/final Results/
> # Inspect the model R Squares
> summary_corp$paths
           CO    CMO     SO   SFO    DF     AP
R^2     0.632  0.380  0.325 0.356 0.581  0.219
AdjR^2  0.622  0.374  0.318 0.349 0.572  0.214
IV      0.382      .      .     .     .      .
II      0.138      .      .     .     .      .
IE      0.059      .      .     .     .      .
HY     -0.141 -0.217 -0.151     .     .      .
EI      0.290      .  0.510     .     .      .
IN          .  0.526      .     .     .      .
PC          .      .      . 0.011     .      .
CX          .      .      . 0.594     .      .
CO          .      .      .     . 0.422      .
CMO         .      .      .     . 0.004      .
SO          .      .      .     . 0.200      .
SFO         .      .      .     . 0.243      .
DF          .      .      .     .     . -0.468
> 
```

VIF values for assess collinearity issues of the structural model. (Source: authors' screenshot from RStudio)

```
R 4.3.2 · ~/PLS Smart/Structural Equation Modeling/R/Information overlaod/final Results/
> # Inspect the structural model collinearity VIF
>
> summary_corp$vif_antecedents
CO :
   IV    II    IE    HY    EI 
1.937 2.354 2.011 1.191 1.857 

CMO :
   HY    IN 
1.066 1.066 

SO :
   EI    HY 
1.082 1.082 

SFO :
   PC    CX 
1.048 1.048 

DF :
   CO   CMO    SO   SFO 
2.623 2.593 1.833 2.385 
```

Path coeffcient estimations, signifcance, and confdence intervals. (Source: au screenshot from RStudio)

```
R 4.3.2 · ~/PLS Smart/Structural Equation Modeling/R/Information overlaod/final Results/
> # Inspect the structural paths
> sum_boot_corp_rep$bootstrapped_paths
              Original Est. Bootstrap Mean Bootstrap SD T Stat. 2.5% CI 97.5% CI
IV   ->  CO           0.382          0.381        0.064   5.958   0.258    0.502
II   ->  CO           0.138          0.138        0.069   1.982  -0.011    0.271
IE   ->  CO           0.059          0.061        0.058   1.016  -0.058    0.171
HY   ->  CO          -0.141         -0.144        0.047  -2.971  -0.238   -0.051
HY   ->  CMO         -0.217         -0.217        0.066  -3.271  -0.338   -0.086
HY   ->  SO          -0.151         -0.151        0.083  -1.813  -0.308    0.016
EI   ->  CO           0.290          0.290        0.073   3.983   0.150    0.440
EI   ->  SO           0.510          0.515        0.058   8.726   0.395    0.628
IN   ->  CMO          0.526          0.529        0.046  11.339   0.434    0.611
PC   ->  SFO          0.011          0.023        0.067   0.165  -0.125    0.141
CX   ->  SFO          0.594          0.595        0.050  11.919   0.490    0.693
CO   ->  DF           0.422          0.424        0.079   5.315   0.264    0.583
CMO   ->  DF          0.004          0.001        0.084   0.053  -0.162    0.169
SO   ->  DF           0.200          0.199        0.067   3.010   0.078    0.332
SFO   ->  DF          0.243          0.245        0.078   3.120   0.093    0.401
DF   ->  AP          -0.468         -0.477        0.063  -7.381  -0.591   -0.343
```

Total effect estimates. (Source: authors' scre from RStudio)

```
R 4.3.2 · ~/PLS Smart/Structural Equation Modeling/R/Information overlaod/final Results/
> # Inspect the total effects
> sum_boot_corp_rep$bootstrapped_total_paths
              Original Est. Bootstrap Mean Bootstrap SD T Stat. 2.5% CI 97.5% CI
IV   ->  CO           0.382          0.381        0.064   5.958   0.258    0.502
IV   ->  DF           0.161          0.161        0.040   3.982   0.092    0.245
IV   ->  AP          -0.075         -0.078        0.026  -2.945  -0.133   -0.036
II   ->  CO           0.138          0.138        0.069   1.982  -0.011    0.271
II   ->  DF           0.058          0.058        0.031   1.875  -0.004    0.118
II   ->  AP          -0.027         -0.028        0.016  -1.691  -0.062    0.002
IE   ->  CO           0.059          0.061        0.058   1.016  -0.058    0.171
IE   ->  DF           0.025          0.025        0.025   0.996  -0.023    0.074
IE   ->  AP          -0.012         -0.012        0.012  -0.941  -0.038    0.011
HY   ->  CO          -0.141         -0.144        0.047  -2.971  -0.238   -0.051
HY   ->  CMO         -0.217         -0.217        0.066  -3.271  -0.338   -0.086
HY   ->  SO          -0.151         -0.151        0.083  -1.813  -0.308    0.016
HY   ->  DF          -0.091         -0.094        0.032  -2.791  -0.163   -0.031
HY   ->  AP           0.042          0.045        0.017   2.476   0.014    0.084
EI   ->  CO           0.290          0.290        0.073   3.983   0.150    0.440
EI   ->  SO           0.510          0.515        0.058   8.726   0.395    0.628
EI   ->  DF           0.225          0.226        0.053   4.200   0.127    0.340
EI   ->  AP          -0.105         -0.108        0.029  -3.589  -0.169   -0.057
IN   ->  CMO          0.526          0.529        0.046  11.339   0.434    0.611
IN   ->  DF           0.002          0.001        0.044   0.053  -0.082    0.092
IN   ->  AP          -0.001         -0.000        0.021  -0.051  -0.044    0.040
PC   ->  SFO          0.011          0.023        0.067   0.165  -0.125    0.141
PC   ->  DF           0.003          0.005        0.017   0.158  -0.032    0.038
PC   ->  AP          -0.001         -0.002        0.008  -0.156  -0.018    0.015
CX   ->  SFO          0.594          0.595        0.050  11.919   0.490    0.693
CX   ->  DF           0.144          0.146        0.050   2.875   0.057    0.252
CX   ->  AP          -0.067         -0.069        0.025  -2.675  -0.125   -0.025
CO   ->  DF           0.422          0.424        0.079   5.315   0.264    0.583
CO   ->  AP          -0.197         -0.204        0.054  -3.644  -0.318   -0.107
CMO   ->  DF          0.004          0.001        0.084   0.053  -0.162    0.169
CMO   ->  AP         -0.002         -0.000        0.040  -0.051  -0.080    0.079
SO   ->  DF           0.200          0.199        0.067   3.010   0.078    0.332
SO   ->  AP          -0.094         -0.094        0.032  -2.898  -0.162   -0.036
SFO   ->  DF          0.243          0.245        0.078   3.120   0.093    0.401
SFO   ->  AP         -0.114         -0.116        0.038  -2.987  -0.194   -0.043
DF   ->  AP          -0.468         -0.477        0.063  -7.381  -0.591   -0.343
>
```

Appendix G

Appendix G Summary of Reviewed Studies and Recommended Strategies

Appendix G provides a summary table the 38 studies included in the systematic review (Chapter 6). The table outlines key information for each study, including citation, methodology, and the principal findings or recommended strategies identified for managing IO

S. No	Citation	Method	Design & Sample	Key Findings
1	Shachaf et al. (2016)	Qualitative	Semi-structured interviews (n = 15)	Four distinct strategies were identified for managing IO: (1) filtering content to reduce information volume, (2) avoiding excessive information exposure, (3) satisfying by accepting adequate rather than optimal solutions, and (4) prioritising readily accessible items by selecting from the top of lists.
2	Soucek and Moser (2010)	Quantitative	Questionnaire (n = 90)	The evaluation study demonstrated that training could effectively improve personal strategies to prevent IO. Specifically, the training intervention enhances the ability to process a certain volume of incoming emails and helps alleviate various aspects of stress related to email communication. The results indicate that the training led to an improvement in knowledge and media competencies.
3	Lauri et al. (2021)	Qualitative	Two focus-group interviews (n = 14) and 17 semi-structured	Research findings highlight that information culture significantly influences how individuals experience IO, with those in open information cultures being more susceptible than those in integrated cultures. Based on these insights, key recommendations include: (1) develop comprehensive organisational information policies that promote structured information sharing and foster trust. (2) Balance formal and informal communication channels while maintaining clear frameworks for critical. (3) Implement targeted information literacy training programs to enhance staff competencies and overcome time management challenges.

S. No	Citation	Method	Design & Sample	Key indings
4	Savolainen (2007)	Qualitative	Interviews (n = 20)	Two key strategies for managing IO were identified: (1) The filtering strategy focuses on systematically eliminating information considered unnecessary, making it particularly suitable for networked information environments. (2) The withdrawal strategy takes a more emotional approach, prioritising self-protection by limiting the number of information sources.
5	Johnson (2014)	Qualitative	Narrative literature	”This study examines four key coping mechanisms (escape, attention, delegation, creative destruction) for IO, analysing each through the lens of seven dosage elements: amount, frequency, sequencing, delivery, contraindications, interactions, and dysfunctions.
6	Aussu (2023)	Qualitative	Interviews (n = 5)	This research significantly advances understanding of information systems by demonstrating the critical importance of software tools and their usage in combating IO within organisations. By examining the impact of tools and providing actionable guidance, this study equips managers with the knowledge necessary to leverage technology effectively to reduce IO, thereby improving employee well-being and organisational performance.

S. No	Citation	Method	Design & Sample	Key indings
7	Stadin et al. (2020)	Qualitative	Critical incident technique (n = 20)	Encourage a positive email culture by promoting effective communication practices. Offer training to enhance individual strategies and competencies in managing emails and software usage. Additionally, ensure access to reliable IT support to address any technical issues promptly and efficiently.
8	Iatraki et al. (2018)	Quantitative	Personal health information recommender	This study proposes the Personal Health Information Recommender, a system that helps patients find high-quality medical information by searching an expert-curated repository. This personalised system aims to address IO by tailoring recommendations based on individual needs and preferences.
9	Saxena and Lamest (2018)	Qualitative	Case study	Findings reveal that managers face challenges due to high volumes of unstructured and rapidly changing information. Common coping strategies include filtering, withdrawal, and summarisation. At the organisational level, this has led to the development and use of interactive dashboards.

S. No	Citation	Method	Design & Sample	Key indings
10	Jia and Wang (2021)	Quantitative	Questionnaire	This paper proposes solutions to help students manage IO, including: (1) credible filtering platforms: develop platforms to help students access reliable and relevant information. (2) Students should uphold values, self-regulate, improve information literacy, and discern right from wrong. (3) enhanced psychological support: improve university support for. (4) students facing the psychological impacts of IO. Information Search Courses: Offer courses to teach students effective information retrieval and evaluation skills.
11	Kozko and Melnikov (2016)	Quantitative	Algorithms	The paper proposed methods and algorithms for analysing forum posts and modifying the forum structure based on its content (Adaptive Discussion Forum). The aim is to improve the efficiency of information handling on the forum and reduce the impact of IO.
12	Cheng and Vassileva (2006)	Quantitative	Questionnaire (n = 31)	the paper suggests that adaptive incentive mechanisms can significantly enhance user participation in online educational communities by aligning individual contributions with community needs, thus mitigating IO and ensuring sustainable engagement

S. No	Citation	Method	Design & Sample	Key indings
13	Gerosa et al. (2001)	Quantitative	Collaborative learning environment	This paper demonstrates that categorising and structuring messages in asynchronous textual communication tools can enhance online course delivery. This approach aids argumentation and encourages participants to reflect on their messages. Despite the increase in the total number of messages, this method reduces IO and improves the quality of discussions. (Filtring)
14	Porcel et al. (2010)	Quantitative	Algorithms	A novel recommender system was developed for University Digital Libraries to combat IO. The system's key innovation is its memory capability, which tracks previously excluded resources. This feature enables the system to reintegrate overlooked materials into future suggestions, which is particularly useful when recommendation options are limited or when users seek diverse resource combinations.

S. No	Citation	Method	Design & Sample	Key indings
15	Mahdi et al. (2020)	Qualitative	Review	The research identifies three primary categories of interventions to address IO: (1) development of theoretical frameworks aimed at reducing IO; (2) improvement of software architecture for enhanced data filtering; (3) assessment of diverse filtering techniques. Results demonstrate that implementing faceted filtering systems proves particularly effective in mitigating IO. .
16	Landale (2007)	Qualitative	-	This paper proposes a proactive, three-step approach to address IO at the individual level: (1) receive and assess the document; (2) develop an initial understanding of the document; and (3) adapt and integrate the new knowledge.
17	Gaudioso et al. (2017)	Quantitative	Questionnaire (n = 242) employees	Coping strategies involve eliminating maladaptive approaches and developing adaptive ones. This can be achieved by increasing awareness and reducing barriers through training, job design, reward systems, peer pressure, and technical support. Additionally, reducing technostress is crucial, which includes measures like prohibiting emails outside of work hours and improving.

S. No	**Citation**	**Method**	**Design & Sample**	**Key indings**
18	Jones and Kelly (2018)	mixed-methods approach	Interview and questionnaires (n = 20)	This paper introduces automated filtering mechanisms designed to algorithmically curate information outputs tailored to users' interests, thus mitigating the issue of IO
19	Ellwart et al. (2015)	Quantitative	Experimental design (n = 363)	The research examines a three-phase STROTA (structured online team adaptation) methodology designed to help virtual teams manage IO. The intervention progresses through distinct stages: beginning with individual situational awareness, advancing to team-wide collective understanding, and culminating in strategic planning.
20	Blummer and M. Kenton (2014)	Qualitative	Literature review	This paper explores five key themes that have emerged from examining the best practices employed by academic librarians to mitigate IO among their users: information presentation, library instruction, user strategies, librarian roles, and software technologies. Moreover, it underscores the importance of information literacy instruction in addressing IO. By empowering users with enhanced research skills, such instruction enables them to improve their search capabilities effectively.

S. No	Citation	Method	Design & Sample	Key indings
21	Tzagarakis et al. (2014)	Quantitative	Adaptive collaboration support	The study examines cognitive complexity in collaboration systems and presents Dicode's solution: an adaptive infrastructure that automatically adjusts to user needs to reduce IO.
22	Liu and Kuo (2016)	Qualitative	Interviews (n = 110)	The research combines the perceived IO framework with the Theory of Planned Behaviour to understand patients' engagement with self-management education. Analysis of personality, subject matter, and regulatory factors offers guidance for healthcare stakeholders in delivering educational content without overwhelming patients.
23	Koen et al. (2018)	Qualitative	Focus group (n = 67)	The study suggested that consumers need simplified nutrition information, more graphics, and less IO.
24	Klerings et al. (2015)	Qualitative	Literature review	Recommendations to solve health IO were proposed: (1) technological solutions; (2) creation or adaptation of filtering systems; (3) improving health literacy; (4) strengthening the individuals' intermediarie

S. No	Citation	Method	Design & Sample	Key indings
25	Gayo-Avello et al. (2003)	Quantitative	Literature review	This study introduces the Cooperative Web, a novel approach to Web Intelligence that eliminates semantics from the web without relying on ontologies, ensuring language autonomy. Unlike the Semantic Web, it leverages individual user browsing experiences to benefit the broader user base, effectively addressing web IO.
26	Turetken and Sharda (2004)	Quantitative	Algorithm	This study addresses the problem of IO in web search results with a two-part solution: (1) developing a system that employs clustering and visualization, including "fisheye views," to reduce data retrieved during searches, and (2) creating a visualization algorithm to enhance user browsing of search results. Together, these efforts aim to minimise data overload and improve user interaction with search results.
27	Huang et al. (2024)	Quantitative	Personalised guide recommendation	This paper employs association rule mining to generate personalised guide recommendation rules based on collective and individual visiting behaviours. The personalised guide recommendation system helps users navigate information efficiently, reducing exposure to overload.

S. No	Citation	Method	Design & Sample	Key indings
28	Clarke et al. (2013)	Qualitative	Literature review	The paper proposes mechanisms to reduce IO for clinicians, including: (1) relevant Resource Access: providing tailored access to job-specific tools like EHRs and clinical databases. (2) Infobuttons: Embedding dynamic, context-sensitive links in EHRs for quick access to pertinent information. (3) Training: Enhancing search skills through training programs for effective use of information retrieval systems.
29	Graf and Antoni (2021)	Quantitative	(n = 25)	The way we receive information can impact how information characteristics contribute to overload. Focusing on information quality, rather than just quantity, might be a better approach to reducing this burden.
30	Lauri and Virkus (2019)	Mixed-methods	Questionnaire (multiple-choice and open-ended questions), n = 16	The study proposes addressing institutional IO through policy development, enhanced information sharing, structured communication practices, and systematic literacy training.

S. No	Citation	Method	Design & Sample	Key indings
31	Zhu and Sun (2023)	Quantitative	Algorithms	The research enhances collaborative filtering algorithms by incorporating information entropy and standard deviation metrics to better differentiate user similarities, thereby improving recommendation accuracy and precision. .
32	Khalid et al. (2021)	Quantitative	Algorithm	The study presents a novel online recommendation algorithm tailored for Massive Open Online Courses, offering a scalable recommender system that addresses the limitations of traditional systems by improving predictive accuracy and classification performance.
33	Lin et al. (2022)	Quantitative	Algorithm	The paper tackles IO in the tourism industry by optimising the traditional collaborative filtering algorithm (CFA) using similarity and correlation factors. It enhances the travel experience with a satisfaction balance strategy. The improved CFA shows the highest average accuracy and recommendation performance, proving useful for user attraction selection and travel company marketing optimisation.

S. No	Citation	Method	Design & Sample	Key indings
34	Wang (2022)	Quantitative	Algorithm	The study tackles IO in MOOC platforms by proposing a mixed collaborative filtering recommendation algorithm on Spark architecture. Key features include collaborative filtering for refined score predictions and optimising weighting factors with a frog-jumping algorithm. Experimental results on music MOOC resources show reduced errors, achieving higher accuracy and efficiency than traditional methods. .
35	Lei et al. (2022)	Quantitative	Algorithm	The paper proposes a personalised recommendation system for outdoor sports to tackle IO. It combines user-based collaborative filtering, project-based collaborative filtering, and content-based recommendation algorithms into a hybrid model. This model, which uses feature expansion and weighted combination, effectively recommends outdoor sports to users and addresses the common cold start problem in recommendation systems.

S. No	Citation	Method	Design & Sample	Key indings
36	Jian et al. (2022)	Quantitative	Algorithm	The paper proposes a Knowledge-Aware Multispace Embedding Learning (KMEL) model to reduce IO in recommender systems. KMEL leverages semantic correlations and high-order semantic collaborative signals across multiple semantic spaces to model users' interests. It integrates semantic embeddings with a target-aware attention mechanism for personalised recommendation
37	Kang and Chung (2022)	quantitative	Algorithm	This paper addresses the issue of IO by helping users find relevant content. This study proposes a new approach that uses a preference tree to predict user preferences in real time. This method improves accuracy and suggests novel content compared to existing systems.
38	Voinea et al. (2020)	Qualitative	Review	The study proposes three key approaches to reduce negative information impacts: strengthening individual capacity, developing enhanced collaborative information organisation systems, and utilising AI-powered assistants to help users navigate online information spaces.

Appendix H

Appendix H: Example of Thematic Analysis Showing Coding Process and Theme Development

This appendix H complements Chapter 6 by showing precisely how the thematic analysis was carried out and by providing worked examples that trace evidence from verbatim extracts through initial codes, subthemes, and final themes. It also records the analytic audit trail and assurance steps used in this research. Corpus: 38 peer-reviewed articles included in the systematic review (see Appendix G).

- Aim of analysis: Identify, organise, and synthesise strategies for managing IOacross sectors.

- Analytic stance: Inductive thematic analysis.

  Worked Walkthrough of the Six Phases (Braun & Clarke)

  This example shows how one extract moved through Phases 1–6 from initial reading to theme development.

Example — Personal Strategies → Filtering & Selective Attention

Source extract

> "Particularly in the net where so much is available, you have to look at the very beginning whether an article is worth reading to the end... the selective approach will be taken there almost automatically." (Savolainen, 2007)

Phase 1: Familiarisation

- Read Savolainen (2007) in print/PDF; highlighted ideas on *early checks* and *front-end screening.*
- Notes were recorded in a structured Excel spreadsheet for easy reference and flexibility. Instead of using qualitative analysis software such as NVivo or Atlas.ti, the coding process was organised in a tabular format within Excel. The spreadsheet included the following columns to ensure transparency and traceability:
  - **Raw Data Excerpt** – the original text segment from the reviewed study.
  - **Initial Code** – a short descriptive label summarising the meaning of the excerpt.
  - **Sub-theme** – the intermediate category grouping related codes.
  - **Theme** – the final overarching category representing a broader pattern.

Phase 2: Generating initial codes

- Codes: `Early screening of sources`; `Selective attention`.

Phase 3: Searching for themes

- Codes clustered with similar actions (e.g., *stop rules*, *satisficing*, *first-pass triage*) across other studies.

* Candidate subtheme label: *Filtering & Selective Attention.*
* **Rationale:** all codes describe intentional narrowing of attention *before* deep processing to reduce overload.

Phase 4: Reviewing themes

* **Internal coherence:** items consistently refer to *early-phase* intake-limiting decisions (e.g., decide early; know when enough is enough).
* **External distinctiveness:** differentiated from *Filtering & Withdrawing* (source reduction/turning off) and *Escape & Avoidance* (delaying or avoiding information altogether).
* **Decision:** retain *Filtering & Selective Attention* as a distinct, cognitively evaluative subtheme.

Phase 5: Defining and naming themes

* **Definition (final):** cognitive strategies for selectively attending to priority inputs and dismissing non-priority inputs at the earliest stage.
* **Naming principle:** draw on my wording ("selective approach", "look at the very beginning") ⇒ subtheme *Filtering & Selective Attention.*

Phase 6: Producing the report

· Used in section 6.4.1; full trace shown in Appendix H.

One-line chain: *Savolainen (2007)* → `Early screening; Selective attention` → *Filtering & Selective Attention* → *Personal Strategies.*

Extract (verbatim)	Initial Codes	Subtheme	Main Theme
Particularly in the net where so much is available, you have to look at the very beginning whether an article is worth reading to the end. So, the selective approach will be taken there almost automatically (Savolainen, 2007).	* Early screening of sources * Selective attention	Filtering and selective attention	Personal strategies
"The problem then is one of focus, monitoring one's environment based on a predetermined set of criteria. Adept decision makers know intuitively when they have gathered enough information for any particular purpose – when enough is enough" (Johnson, 2014).	Satisficing	Filtering and selective attention	Personal strategies
"The problem then is one of focus, monitoring one's environment based on a predetermined set of criteria."	Focus on criteria	Filtering and selective attention	Personal strategies
Managers used a combination of filtering, withdrawal and summarising strategies… keeping the number of information sources at a minimum.	Source minimisation	Filtering and withdrawing	Personal strategies

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Extract (verbatim)	Initial Codes	Subtheme	Main Theme
"Avoiding and Withdrawing... ignoring potentially useful information... or keeping to a minimum the number of sources to be considered." (Bawden and Robinson, 2020).	Information withdrawal	Filtering and withdrawing	Personal strategies
"Examples of withdrawal are: customising social media... unfriending... turning off mobile devices." (Bawden and Robinson, 2020).	Digital disengagement	Filtering and withdrawing	Personal strategies
"If the list of results remained very long... they focused on the first part of the list." (Shachaf et al., 2016).	Skimming top results	Filtering and selective attention	Personal strategies
"When the list of results remained very long ... I focused on the first part of the list and selected relevant items. Once I found the required number of items I stopped the search."	∗ Stopping early ∗ Avoiding full review ∗ Managing pressure	Escape and Avoidance Strategies	Personal strategies

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Extract (verbatim)	Initial Codes	Subtheme	Main Theme
"We define information avoidance as any behavior intended to prevent or delay the acquisition of available but potentially unwanted information." (Sweeny et al., 2010).	Prevent/delay unwanted	Escape & Avoidance	Personal strategies
"People may avoid information with the intention of learning the information later, or they may decide to avoid the information altogether." (Sweeny et al., 2010).	Permanent avoidance	Escape & Avoidance	Personal strategies
"Information may demand a change in beliefs. . . "	Belief protection	Escape and Avoidance Strategies	Personal strategies
"Avoiding information. . . may cause unpleasant emotions or diminish pleasant emotions."	Emotion regulation	Escape and Avoidance Strategies	Personal strategies
"By bringing the most important information in a single place, dashboards enable performance monitoring and support decision making." (Saxena and Lamest, 2018).	Interactive visual aggregation	Information Systems and Dashboards	Organisational and Technological Solutions

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Extract (verbatim)	**Initial Codes**	**Subtheme**	**Main Theme**
"Dashboards are useful for summarising data and alleviating information overload by utilising robust visualisation principles." (Alhamadi, 2020).	Summarising to reduce IO	Information Systems and Dashboards	Organisational and Technological Solutions
"we describe the algorithms and methods of forum restructuring aimed at simplifying the user's work and reducing the information overload for the user." (Kozko and Melnikov, 2016).	Algorithmic restructuring to reduce IO	Algorithms and Recommender Systems	Organisational and Technological Solutions
"we propose an improved recommender system to avoid the persistent information overload found in a University Digital Library"	Recommender system for persistent IO	Algorithms and Recommender Systems	Organisational and Technological Solutions
"The idea is to include a memory to remember selected resources but not recommended to the user, and in such a way, the system could incorporate them in future recommendations . . . "	Memory augmented recommender	Algorithms and Recommender Systems	Organisational and Technological Solutions

Continued on next page

Extract (verbatim)	**Initial Codes**	**Subtheme**	**Main Theme**
"Information literacy in the workplace context is defined as a set of abilities for employees to recognize when information is needed and to locate, evaluate, organize and use information effectively, as well as the abilities to create, package and present information effectively to the intended audience." (Cheuk, 2008).	Workplace information literacy; Use & creation of information	Information Literacy and Education	Organisational and Technological Solutions
"After the launch of Minerva, all 3,000 staff were given a 60 minute training… The aim was to provide basic information literacy training and ensure all staff have the skills to use the new tools." (Cheuk, 2008).	Capacity building; Tool skills	Information Literacy and Education	Organisational and Technological Solutions
"A training intervention was developed and evaluated… aimed to cope with information overload in email communication by improving media competencies, workflow, and email literacy."	Email management training	Training and Skill Development	Organisational and Technological Solutions

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Extract (verbatim)	**Initial Codes**	**Subtheme**	**Main Theme**
"Needs relating to digital literacy facilitation involved, for instance, practical training in managing ICT, preferably with a mentor available for questions and support." (Stadin et al., 2020).	Digital literacy training	Training and Skill Development	Organisational and Technological Solutions
"Formal and regular information sharing and communication were perceived as supportive to overcome information overload." (Lauri et al., 2021).	∗ Formal communication norms ∗ Scheduled meetings and memos	Cultural and Policy Adjustments	Communication and Information Sharing
"Organisational information management is the key to effective coping with information overload." (Lauri et al., 2021).	Organizational information management policy	Cultural and Policy Adjustments	Communication and Information Sharing

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Extract (verbatim)	Initial Codes	Subtheme	Main Theme
"The largest portion of respondents indicated that they preferred publications and information that were recommended to them by their teachers, trainers, or persons they trust." (Koen et al., 2018).	Reliance on trusted recommendations	Recommendations and Simplified Information	Communication and Information Sharing
"Consumers struggled to understand the information on labels, specifically the nutrition information table" (Koen et al., 2018).	Need for plain language	Recommendations and Simplified Information	Communication and Information Sharing

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