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ATTENTION ECONOMY AS A SOURCE OF MARKET FAILURE:
A CAUSAL ANALYSIS OF DIGITAL EXTERNALITIES IN THE FORM OF PRODUCTIVITY LOSS AND MENTAL HEALTH IMPACTS

Thesis Submitted
in Partial Fulfillment of the Requirements for the Degree of

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in
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by

Divya Sharma
(Roll No. 24/MAE/57)

Under the Supervision of

Prof. Amit Mookherjee
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Any errors or omissions in this dissertation are solely my responsibility.

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CANDIDATE'S DECLARATION

I, **Divya Sharma**, hereby certify that the work which is being presented in the thesis entitled **"Attention Economy as a Source of Market Failure: A Causal Analysis of Digital Externalities in the Form of Productivity Loss and Mental Health Impacts"** in partial fulfillment of the requirements for the award of the Degree of Master of Arts in Economics, submitted in the Department of Economics, Delhi Technological University, is an authentic record of my own work carried out during the period from **10 July 2025 to June 2026** under the supervision of **Prof. Amit Mookherjee**.

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List of Symbols and Abbreviations

Abbreviation	Description
DA	Digital Access
AS	Asymmetric Information
SUI	Screen Use Intensity
SA	Screen Addiction
IP	Impact on Productivity
MH	Mental Hygiene
EFA	Exploratory Factor Analysis
PLS-SEM	Partial Least Squares Structural Equation Modelling
AVE	Average Variance Extracted
CR	Composite Reliability
ρ_A	Dijkstra-Henseler's Reliability Coefficient (rho_A)
ρ_C	Composite Reliability Coefficient (rho_C)
VIF	Variance Inflation Factor
SRMR	Standardized Root Mean Square Residual
NFI	Normed Fit Index
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
R^2	Coefficient of Determination
f^2	Effect Size
Q^2	Predictive Relevance (Stone-Geisser's Q²)
SPSS	Statistical Package for the Social Sciences

ATTENTION ECONOMY AS A SOURCE OF MARKET FAILURE: A CAUSAL ANALYSIS OF DIGITAL EXTERNALITIES IN THE FORM OF PRODUCTIVITY LOSS AND MENTAL HEALTH IMPACTS

Divya Sharma

ABSTRACT

The rapid expansion of digital technologies has transformed attention into a valuable economic resource, with digital platforms increasingly competing for user engagement through personalised content, algorithmic recommendations, and behavioural tracking. While these developments have enhanced connectivity and access to information, they have also raised concerns regarding excessive digital engagement, productivity loss, and broader welfare implications. Against this backdrop, the present study investigates whether the attention economy contributes to market failure by examining how Digital Access and Asymmetric Information influence Screen Use Intensity and Screen Addiction, and how these behavioural outcomes subsequently affect Productivity and Mental Hygiene.

The study is grounded in Attention Economy Theory, Information Asymmetry Theory, Behavioural Economics, and Market Failure Theory. A conceptual framework was developed to analyse the relationships among the study variables. Primary data were collected from 174 digital users through a structured questionnaire. Exploratory Factor Analysis (EFA) was employed to examine the underlying factor structure of the measurement instrument, while Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to assess the measurement model, structural relationships, mediation effects, and moderation effects.

The findings reveal that both Digital Access and Asymmetric Information significantly increase Screen Use Intensity and Screen Addiction. The results indicate that individuals with greater access to digital technologies and those operating in environments characterised by higher informational imbalances are more likely to engage intensively with digital platforms and develop addictive patterns of usage. Among the determinants examined, Asymmetric Information emerged as a particularly important factor influencing digital behaviour, highlighting the role of platform-controlled information, personalised recommendations, and algorithmic engagement mechanisms.

A key finding of the study is the distinction between Screen Use Intensity and Screen Addiction. While Screen Use Intensity did not significantly affect either Productivity or Mental Hygiene, Screen Addiction exerted a strong and significant influence on Productivity and emerged as the primary behavioural mechanism linking digital market conditions to adverse outcomes. The mediation analysis further confirmed that Screen Addiction significantly mediates the effects of Digital Access and Asymmetric Information on Productivity, whereas Screen Use Intensity does not function as a significant mediator. The moderation analysis revealed that Asymmetric Information

significantly moderates the relationship between Digital Access and Screen Use Intensity but does not significantly moderate the relationship between Digital Access and Screen Addiction.

The study concludes that the attention economy contributes to market failure primarily through informational asymmetries and addiction-driven engagement rather than through digital usage alone. The findings suggest that productivity-related welfare losses arise when digital engagement develops into behavioural dependency, creating a divergence between private platform incentives and broader social welfare outcomes. By integrating perspectives from attention economy, information asymmetry, and behavioural economics literature, the study contributes to a deeper understanding of how digital platforms shape user behaviour and economic outcomes. The findings also offer important implications for platform governance, algorithmic transparency, digital well-being policies, and regulatory interventions aimed at fostering a more balanced and welfare-enhancing digital ecosystem.

Keywords: Attention Economy, Digital Access, Asymmetric Information, Screen Use Intensity, Screen Addiction, Productivity, Mental Hygiene, Market Failure, PLS-SEM.

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Chapter 1

INTRODUCTION

1.1 Background of the Study

The rapid advancement of digital technologies has transformed the manner in which individuals communicate, conduct business, access information, and participate in economic activities. Over the past two decades, the digital economy has expanded significantly due to the widespread adoption of the internet, smartphones, cloud computing, and, more recently, artificial intelligence. These developments have created new forms of production, consumption, and value creation. In contemporary economies, digital platforms such as social media networks, search engines, video-streaming services, and e-commerce marketplaces have become central intermediaries in everyday life, influencing communication, learning, work, and decision-making processes. Chaffey and Ellis-Chadwick (2019) observed that digital platforms increasingly shape consumer interactions and have become integral to modern economic activity.

The unprecedented growth in information availability has, however, generated a paradox. While digital technologies have made information more accessible than ever before, human attention remains inherently limited. Herbert Simon (1971) was among the first scholars to recognize this challenge, arguing that an abundance of information creates a scarcity of attention. According to Simon (1971), the increasing supply of information consumes the attention of its recipients, making attention itself a scarce and valuable resource. This insight laid the foundation for what later became known as the Attention Economy.

The concept of the Attention Economy gained prominence as digital platforms increasingly realized that attracting and retaining user attention constituted the basis of their business models. Goldhaber (1997) argued that in the Information Age, attention had emerged as a new form of currency, with individuals and organizations competing for visibility, recognition, and engagement. Building upon this idea, Wu (2016) described modern digital platforms as "attention merchants" whose primary objective is to capture, retain, and monetize human attention. Unlike traditional firms that compete mainly for physical resources, digital platforms compete for users' time, attention, and cognitive engagement.

The rise of algorithm-driven platforms has further intensified this competition. Social media applications such as Facebook, Instagram, YouTube, TikTok, and X (for-

merly Twitter) employ sophisticated recommendation systems, personalized feeds, autoplay features, infinite scrolling mechanisms, and push notifications to maximize user engagement. Wu (2016) explained that these technological designs are specifically intended to prolong user interaction and increase engagement. Similarly, Zuboff (2019) argued that digital platforms continuously adapt their systems to user behaviour, thereby encouraging longer periods of platform usage. Through such mechanisms, user attention is transformed into an economic asset that can be monetized through targeted advertising and other commercial activities.

Attention has therefore become a central component of value creation in digital markets. Most digital platforms operate on advertising-based business models in which revenue generation depends directly on user engagement. The longer users remain on a platform, the greater the opportunities for data collection, targeted advertising, and revenue generation. Zuboff (2019) argued that this process extends beyond conventional advertising and forms part of a broader system of surveillance capitalism in which user behaviour is continuously monitored, predicted, and monetized. Consequently, attention has evolved into a strategic economic resource that significantly influences platform profitability and market valuation.

While attention-based business models have generated substantial economic value, they have also raised concerns regarding their broader social and economic consequences. Twenge and Campbell (2018) reported that excessive engagement with digital platforms is associated with declining psychological well-being among users. Likewise, Hendricks and Vestergaard (2019) highlighted the growing risks of compulsive digital behaviour, reduced concentration, sleep disturbances, and increasing psychological stress arising from digital environments. Many platform features are intentionally designed to encourage continuous engagement, potentially fostering behavioural dependency and reducing individuals' ability to regulate their digital consumption.

These concerns can be examined through the economic framework of market failure. Market failure occurs when markets fail to allocate resources efficiently, resulting in outcomes that are not socially optimal. One important source of market failure is the presence of negative externalities, where the costs associated with an economic activity are borne by third parties and are not reflected in market prices. Digital platforms benefit from increased user engagement; however, many of the associated costs—including productivity losses, mental health challenges, and diminished cognitive well-being—are borne by users, their families, employers, and society at large. As a result, the private incentives of digital platforms may diverge from broader social welfare objectives.

Another potential source of market failure arises from information asymmetry. Users often possess limited knowledge regarding how their attention is captured, analysed, and monetized, whereas digital platforms possess extensive information about user behaviour, algorithmic operations, and engagement strategies. Zuboff (2019) argued that this imbalance of information allows platforms to exercise considerable influence over user decisions while limiting users' understanding of the mechanisms shaping their digital experiences. Consequently, consumers may engage more extensively with attention-capturing digital services than they would under conditions of complete information, leading to inefficient market outcomes.

These issues are particularly relevant in the Indian context. India represents one of the world's largest and fastest-growing digital markets, with hundreds of millions of internet users and rapidly increasing smartphone penetration. Government initiatives such as Digital India, combined with declining data costs and widespread mobile internet access, have accelerated the adoption of digital technologies across both urban and rural populations. At the same time, concerns regarding excessive screen time, digital addiction, declining productivity, and deteriorating mental health have become increasingly prominent among students, professionals, and young adults.

Despite the growing significance of these concerns, empirical research examining the Attention Economy from the perspective of behavioural economics and market failure remains limited in India. Existing studies primarily focus on the relationship between digital usage and behavioural outcomes, while relatively few investigate the underlying mechanisms through which digital platforms influence user behaviour. In particular, there remains limited empirical evidence regarding the roles of screen addiction, information asymmetry, and digital access in generating broader social costs.

Given the increasing importance of the Attention Economy and the limited empirical evidence available in the Indian context, a systematic investigation is warranted. This study seeks to address this gap by examining the relationships among Digital Access, Asymmetric Information, Screen Use Intensity, Screen Addiction, Productivity Loss, and Mental Health Impact. By analysing these relationships, the study aims to enhance understanding of the behavioural and economic dynamics underlying digital markets and to evaluate whether the Attention Economy generates negative externalities and information asymmetries that contribute to market failure.

1.2 Statement of the Problem

The attention economy has emerged as a dominant feature of contemporary digital markets. However, existing research has largely focused on descriptive and correlational relationships between digital technology use and behavioural outcomes. There remains limited empirical evidence regarding the causal mechanisms through which digital access contributes to screen addiction, productivity loss, and adverse mental health outcomes. Furthermore, much of the existing literature has been conducted in Western contexts, leaving the Indian digital ecosystem comparatively underexplored. Twenge and Campbell (2018), Wu (2016), and Zuboff (2019) highlighted the growing influence of digital platforms on individual behaviour, yet important questions regarding the economic implications of these developments remain insufficiently addressed.

In the digital era, platform providers increasingly employ algorithm-driven engagement mechanisms designed to capture and retain user attention. Personalized recommendations, autoplay features, push notifications, and infinite scrolling interfaces encourage prolonged user engagement and generate substantial advertising revenues for platform owners. While these practices create significant private benefits for digital firms, many of the associated social costs are borne by users and society. Such costs include excessive screen usage, addictive digital behaviour, productivity losses, and adverse mental health outcomes. This divergence between private benefits and social costs raises concerns regarding market failure in the form of negative externalities. Wu

(2016), Zuboff (2019), and Hendricks and Vestergaard (2019) argued that attention-capturing digital environments may generate welfare losses that are not fully reflected in market transactions.

A further concern arises from information asymmetry. Digital platforms possess extensive information regarding user behaviour, engagement patterns, and algorithmic design, whereas users often have limited knowledge of how their attention is captured, manipulated, and monetized. Akerlof (1970) demonstrated that information asymmetries can result in inefficient market outcomes when one party possesses substantially more information than another. In the context of digital markets, this imbalance may impair users' ability to make fully informed decisions regarding their digital consumption, thereby contributing to excessive engagement and inefficient allocation of attention resources.

Despite the growing importance of these concerns, empirical research examining the pathways through which digital access influences behavioural and economic outcomes remains limited. In particular, there is insufficient evidence regarding the mediating roles of Screen Use Intensity and Screen Addiction, as well as the moderating influence of Asymmetric Information. Consequently, a comprehensive behavioural-economic framework that simultaneously incorporates these constructs is required to better understand the mechanisms through which the attention economy affects individual welfare. Goldhaber (1997), Wu (2016), and Newman et al. (2021) emphasized the need for further investigation into the economic and behavioural consequences of attention-driven digital environments.

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To address this gap, the present study employs Partial Least Squares Structural Equation Modelling (PLS-SEM) to examine the direct, indirect, and moderating relationships among Digital Access, Screen Use Intensity, Screen Addiction, Productivity Loss, Mental Health Impact, and Asymmetric Information within the Indian digital ecosystem. The study seeks to provide empirical evidence regarding whether the attention economy contributes to market failure through the generation of negative externalities and information asymmetries. By doing so, it aims to enhance understanding of the behavioural and economic consequences of attention-based digital business models and their implications for social welfare.

1.3 Research Gap

Although the Attention Economy has attracted increasing scholarly attention in recent years, several important theoretical, empirical, and contextual gaps remain unresolved. Existing research has contributed significantly to understanding digital engagement, platform-based business models, and online consumer behaviour; however, the mechanisms through which attention-driven digital environments generate broader economic and social consequences remain insufficiently explored.

First, a substantial proportion of the existing literature focuses on identifying correlations between digital technology use and outcomes such as mental health, well-being, and productivity. Studies have frequently reported associations between excessive screen usage and adverse psychological outcomes, including anxiety, depression, reduced life satisfaction, and diminished well-being. Twenge and Campbell (2018),

for example, documented significant relationships between screen time and psychological well-being among adolescents. However, relatively few studies have examined the causal pathways through which digital access and platform engagement translate into these outcomes. Consequently, the behavioural mechanisms linking digital market conditions to social costs remain inadequately understood.

Second, much of the Attention Economy literature has been developed within Western countries, particularly the United States and Europe. Foundational contributions by Simon (1971), Goldhaber (1997), Wu (2016), and Zuboff (2019) primarily examine digital platforms and user behaviour within Western institutional, technological, and socio-economic contexts. While these studies provide valuable theoretical insights, their applicability to emerging digital economies such as India remains insufficiently tested. Given India's rapid digital transformation, widespread smartphone adoption, and expanding internet penetration, there is a need for empirical evidence that reflects the realities of the Indian digital ecosystem.

Third, there is a limited body of research employing comprehensive causal modelling approaches to examine the Attention Economy. Existing studies frequently rely on descriptive analyses, regression-based models, or simple correlational techniques. Although these approaches provide useful insights, they may not adequately capture the complex relationships among multiple latent constructs, mediating mechanisms, and moderating effects. In particular, there is a scarcity of studies that simultaneously examine Digital Access, Asymmetric Information, Screen Use Intensity, Screen Addiction, Productivity Loss, and Mental Health Impact within a unified analytical framework. This highlights the need for advanced analytical techniques such as Partial Least Squares Structural Equation Modelling (PLS-SEM), which allows the estimation of direct, indirect, and moderating relationships among latent variables.

Fourth, while algorithms play a central role in shaping user engagement, they are rarely examined as economic forces influencing resource allocation and market outcomes. Existing studies typically discuss algorithms as technological tools designed to improve user experience and engagement. However, algorithms also influence attention allocation, consumer decision-making, and platform profitability. As a result, the economic implications of algorithm-driven attention capture remain underexplored, particularly from the perspective of market failure and welfare economics.

Fifth, the role of information asymmetry in digital markets has received comparatively limited empirical attention. Digital platforms possess extensive information regarding user behaviour, engagement patterns, and algorithmic optimization strategies, whereas users often have limited awareness of how their attention is captured, influenced, and monetized. Akerlof (1970) demonstrated that information asymmetries can lead to inefficient market outcomes when one party possesses substantially greater information than another. Despite its relevance to digital markets, the concept has rarely been incorporated into empirical studies of the Attention Economy, particularly in relation to behavioural outcomes such as Screen Addiction, Productivity Loss, and Mental Health Impact.

Finally, there is a notable shortage of empirical evidence examining the Attention Economy from a behavioural-economic perspective within the Indian context. Existing Indian studies largely focus on descriptive measures of internet usage, social

media consumption, or general well-being indicators. Relatively few studies investigate the mechanisms through which attention-based digital business models generate social costs and welfare losses. Consequently, important questions regarding the relationship between digital access, information asymmetry, addictive digital behaviour, productivity loss, and mental health remain insufficiently addressed.

The present study seeks to address these gaps by developing and empirically testing a comprehensive behavioural-economic framework that integrates Digital Access, Asymmetric Information, Screen Use Intensity, Screen Addiction, Productivity Loss, and Mental Health Impact. By employing PLS-SEM within the Indian digital ecosystem, the study contributes to the literature by examining the causal mechanisms through which the Attention Economy may generate negative externalities and information asymmetries that contribute to market failure.

1.4 Research Objectives

The present study aims to examine the behavioural-economic implications of the Attention Economy and its role in generating market failure. Specifically, the study seeks to:

1. To examine the influence of Digital Access on Screen Use Intensity and Screen Addiction among digital users.
2. To investigate the role of Asymmetric Information in shaping user engagement and addictive digital behaviour within the Attention Economy.
3. To analyse the effects of Screen Use Intensity and Screen Addiction on Productivity Loss and Mental Health Impact.
4. To evaluate whether Productivity Loss and Mental Health Impact constitute negative externalities generated by the Attention Economy and thereby contribute to market failure.
5. To examine the moderating role of Asymmetric Information in the relationship between Digital Access and digital engagement outcomes, namely Screen Use Intensity and Screen Addiction.
6. To propose policy recommendations relating to algorithmic transparency, ethical platform design, digital literacy, and regulatory interventions for mitigating the adverse consequences of the Attention Economy.

1.5 Research Questions

The present study seeks to address the following research questions:

1. How does Digital Access influence Screen Use Intensity among digital users?
2. How does Digital Access influence Screen Addiction among digital users?

3. What is the effect of Asymmetric Information on Screen Use Intensity?
4. What is the effect of Asymmetric Information on Screen Addiction?
5. What is the effect of Screen Use Intensity on Productivity Loss?
6. What is the effect of Screen Use Intensity on Mental Health Impact?
7. What is the effect of Screen Addiction on Productivity Loss?
8. What is the effect of Screen Addiction on Mental Health Impact?
9. Does Asymmetric Information moderate the relationship between Digital Access and Screen Use Intensity?
10. Does Asymmetric Information moderate the relationship between Digital Access and Screen Addiction?
11. To what extent do Productivity Loss and Mental Health Impact constitute negative externalities generated by the Attention Economy and contribute to market failure?
12. What policy interventions can be adopted to mitigate the adverse effects of attention-driven digital markets while promoting digital well-being and social welfare?

1.6 Definition of Key Terms and Theoretical Foundations

1.6.1 Attention Economy

The rise of digital technologies has transformed the nature of economic value creation and exchange. In contemporary digital environments, attention has emerged as a scarce and highly contested resource. Although information is abundant and continuously expanding, individuals remain constrained by limited cognitive capacity. Consequently, digital platforms, advertisers, and content creators compete intensively to capture and sustain user attention, which can subsequently be monetized through advertising, data extraction, and platform-driven market power. This phenomenon is widely conceptualized as the Attention Economy. Simon (1971) argued that an abundance of information creates a scarcity of attention, while Goldhaber (1997) identified attention as a new form of economic currency in the Information Age.

Within this framework, attention is not merely a psychological construct but an economic asset. Digital platforms systematically design engagement mechanisms to maximize user interaction, retention, and monetization.

Operational Definition: Attention Economy refers to an economic system in which human attention functions as a scarce resource that is captured, managed, and monetized by digital platforms.

1.6.2 Digital Access (DA)

Digital Access refers to an individual's ability to participate in digital ecosystems through access to technological infrastructure and connectivity. It encompasses access to smartphones, computers, internet services, and digital platforms that facilitate communication, information acquisition, and socio-economic participation. According to Van Dijk (2020), inequalities in digital access significantly influence individuals' opportunities and engagement within digital environments.

Operational Definition: Digital Access refers to the extent to which individuals possess the technological resources and connectivity required to engage with digital platforms and services.

1.6.3 Screen Use Intensity (SUI)

Screen Use Intensity reflects the degree of engagement with digital devices in terms of frequency and duration of usage. Such engagement may include communication, entertainment, social networking, education, and work-related activities. Within the Attention Economy, Screen Use Intensity serves as an indicator of how individuals allocate their attention across digital environments. Twenge and Campbell (2018) highlighted the growing significance of screen exposure in shaping behavioural outcomes.

Operational Definition: Screen Use Intensity refers to the frequency and duration of engagement with digital devices across various online activities.

1.6.4 Screen Addiction (SA)

Screen Addiction refers to excessive and compulsive engagement with digital devices that persists despite awareness of its adverse consequences. Individuals exhibiting screen addiction often experience difficulty in regulating usage patterns, disengaging from digital environments, and maintaining a balance between online and offline activities. Kuss and Griffiths (2017) emphasized that behavioural addictions associated with digital technologies share characteristics similar to other forms of addictive behaviour.

Within the Attention Economy, addictive patterns of engagement may be reinforced by platform features designed to maximize user retention and repeated interaction.

Operational Definition: Screen Addiction refers to persistent and compulsive use of digital devices characterized by reduced self-control and difficulty disengaging from digital activities.

1.6.5 Productivity Loss (PL)

Productivity refers to the efficient utilization of time, effort, and cognitive resources to achieve desired outcomes. In digital environments, excessive engagement, multitasking demands, and continuous interruptions may reduce concentration and task efficiency. Mark et al. (2018) argued that frequent digital interruptions can significantly impair workplace and academic performance.

Operational Definition: Productivity Loss refers to reductions in concentration,

efficiency, and task completion resulting from excessive engagement with digital environments.

1.6.6 Mental Health Impact (MHI)

Mental Health Impact refers to the psychological consequences associated with excessive or maladaptive digital engagement. Research has linked prolonged exposure to digital environments with stress, anxiety, emotional exhaustion, sleep disturbances, and reduced psychological well-being. The World Health Organization (2022) emphasized the growing importance of understanding the mental health implications of digital lifestyles.

Operational Definition: Mental Health Impact refers to adverse psychological outcomes such as stress, anxiety, emotional fatigue, sleep disruption, and reduced well-being associated with excessive digital engagement.

1.6.7 Asymmetric Information (AS)

Information asymmetry exists when one party in an economic relationship possesses significantly greater information than another. In digital markets, platforms typically hold extensive information regarding user behaviour, engagement patterns, and algorithmic processes, whereas users possess limited knowledge of how their attention and personal data are collected and monetized. Akerlof (1970) demonstrated that such informational imbalances can result in inefficient market outcomes.

Operational Definition: Asymmetric Information refers to the unequal distribution of information between digital platforms and users regarding data collection, algorithmic processes, and attention monetization practices.

1.6.8 Market Failure

Market Failure occurs when market mechanisms fail to allocate resources efficiently, resulting in outcomes that do not maximize social welfare. According to Stiglitz (2000), market failures commonly arise from externalities, information asymmetries, and market power. Within digital attention markets, market failure may occur when platforms maximize engagement and profit while imposing unaccounted social costs on users and society.

Operational Definition: Market Failure refers to inefficient market outcomes arising from the inability of digital markets to internalize the social costs associated with attention-driven business models.

1.6.9 Negative Externalities

Negative externalities arise when the actions of economic agents impose costs on third parties that are not reflected in market prices. Pigou (1920) identified externalities as a major source of market inefficiency. In digital ecosystems, negative externalities may

manifest in the form of productivity loss, psychological stress, reduced well-being, and other social costs associated with excessive platform engagement.

Operational Definition: Negative Externalities refer to the social and psychological costs generated by attention-driven digital activities that are not borne directly by digital platforms.

1.6.10 Psychology of Attention

Understanding the Attention Economy requires an examination of the psychological mechanisms that govern human attention. Although individuals are continuously exposed to vast amounts of information, their cognitive capacity to process such information remains inherently limited. Consequently, attention functions as a scarce cognitive resource that filters information and determines which stimuli enter conscious awareness and influence behaviour. Simon (1971) argued that while information may be abundant, human attention remains limited, thereby making attention an increasingly valuable resource in modern economies.

Research in cognitive psychology suggests that attention is not allocated solely on the basis of rational evaluation. Rather, it is strongly influenced by biological, emotional, and evolutionary factors. Information perceived as personally relevant, emotionally stimulating, novel, or connected to fundamental human needs is more likely to attract attention than neutral information. Davenport and Beck (2001) argued that individuals naturally allocate attention to stimuli that appear meaningful to their personal circumstances, interests, and goals.

From an evolutionary perspective, selective attention served an important adaptive function. Early humans who were able to rapidly identify threats, opportunities, social signals, and survival-related information were more likely to survive and reproduce. Consequently, the human brain evolved to prioritize information associated with safety, health, social belonging, status, and personal identity. Maslow (1943) similarly emphasized that human behaviour is shaped by the pursuit of needs ranging from physiological survival to self-actualization. These deeply rooted psychological tendencies continue to influence attention allocation in contemporary digital environments.

A particularly important characteristic of human attention is its self-referential nature. Individuals are generally more responsive to information that appears directly relevant to their own experiences, preferences, and circumstances. Davenport and Beck (2001) noted that successful attention management depends upon understanding that people are naturally drawn to information that enhances self-understanding or addresses personally significant concerns. This tendency provides a psychological foundation for the widespread use of personalization strategies in digital markets.

Digital platforms increasingly rely on data collection, behavioural tracking, and algorithmic analysis to deliver personalized content, advertisements, and recommendations. By tailoring information to individual users, platforms increase the likelihood of engagement and interaction. Zuboff (2019) argued that such practices form part of a broader system in which user behaviour is continuously monitored and utilized to predict and influence future actions. Personalized recommendations, targeted advertising, and algorithmically curated feeds therefore capitalize on the human preference

for self-relevant information and contribute to prolonged user engagement.

The commercialization of attention is closely linked to these psychological mechanisms. Digital platforms employ notifications, personalized feeds, autoplay functions, infinite scrolling interfaces, and recommendation algorithms because these features align with fundamental cognitive and emotional drivers of human behaviour. Wu (2016) described modern digital platforms as attention merchants that compete for users' limited attention through increasingly sophisticated engagement strategies. By continuously presenting users with psychologically stimulating and personally relevant content, platforms enhance engagement, prolong screen time, and increase opportunities for monetization.

The psychology of attention provides an important theoretical foundation for the present study because it helps explain why individuals become increasingly engaged with digital platforms and why excessive engagement may develop into addictive patterns of behaviour. It further demonstrates that attention allocation is not always the outcome of fully rational decision-making but is frequently shaped by cognitive limitations, behavioural biases, and biological predispositions. From a behavioural-economic perspective, these characteristics make users susceptible to persuasive platform designs that exploit predictable patterns of human behaviour. This perspective supports the broader argument that digital markets may generate inefficient outcomes when platform incentives capitalize on psychological vulnerabilities, thereby contributing to information asymmetry, negative externalities, and market failure (Akerlof, 1970; Stiglitz, 2000).

1.7 Conclusion

This chapter introduced the concept of the Attention Economy and examined its growing significance within contemporary digital markets. The discussion highlighted how the rapid expansion of digital technologies and platform-based business models has transformed human attention into a valuable economic resource. In an increasingly information-rich environment, digital platforms compete intensively for user attention through algorithm-driven engagement strategies, creating substantial economic value while simultaneously raising concerns regarding excessive screen use, addictive digital behaviour, productivity loss, and adverse mental health outcomes.

The chapter further examined these concerns from a behavioural-economic perspective by emphasizing the potential existence of market failure arising from negative externalities and information asymmetry. While digital platforms derive considerable benefits from increased user engagement, many of the associated social and psychological costs are borne by users and society. The review of the contemporary digital environment highlighted the growing importance of understanding how platform design, information asymmetries, and behavioural vulnerabilities influence user outcomes.

In response to these concerns, the chapter identified important gaps in the existing literature, including the limited availability of causal evidence, the predominance of Western-focused studies, and the lack of comprehensive research examining the behavioural-economic implications of the Attention Economy. To address these gaps, the study formulated its research objectives, research questions, hypotheses, and

conceptual framework. The chapter also established the rationale for examining the relationships among Digital Access, Asymmetric Information, Screen Use Intensity, Screen Addiction, Productivity Loss, and Mental Health Impact.

Overall, the chapter provides the conceptual foundation for investigating whether the Attention Economy generates negative externalities and contributes to market failure through attention-driven digital engagement. Having established the context, significance, and direction of the study, the next chapter reviews the relevant theoretical and empirical literature relating to the Attention Economy, information asymmetry, digital engagement, behavioural addiction, and market failure. This review forms the basis for the development of the conceptual framework and hypotheses tested in the study.

Chapter 2

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Introduction

The Attention Economy has emerged as one of the most significant developments in the digital era, reshaping the manner in which individuals consume information, interact with technology, and participate in economic activities. As digital platforms increasingly rely on user engagement as a primary source of value creation, understanding the mechanisms through which attention is captured, sustained, and monetized has become an important area of academic inquiry. The growing influence of social media platforms, search engines, streaming services, and other digital applications has intensified competition for user attention, making it necessary to examine the broader economic and social implications of these developments.

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The purpose of this chapter is to critically review the theoretical and empirical literature relevant to the Attention Economy and its consequences for individual and societal welfare. The review examines how digital platforms employ engagement-driven strategies to influence user behaviour and how these strategies may contribute to Screen Use Intensity, Screen Addiction, Productivity Loss, and Mental Health Impact. By synthesizing existing research, the chapter identifies the key concepts, theoretical foundations, and empirical findings that support the present study.

Given the complexity of the Attention Economy, a multidisciplinary perspective is required. From an economic standpoint, attention is treated as a scarce resource that is increasingly commodified and traded within digital markets. Simon (1971) argued that an abundance of information creates scarcity of attention, while Goldhaber (1997) described attention as a form of currency in the information age. Psychological perspectives explain how persuasive technologies, behavioural reinforcement, and habit formation influence user engagement and addictive digital behaviour. Technological perspectives further explain how algorithms, recommendation systems, and platform architectures are designed to maximize user attention and interaction. Wu (2016) and Zuboff (2019) emphasized that contemporary digital platforms use sophisticated systems to capture, predict, and monetize user behaviour.

The literature also highlights growing concerns regarding the unintended conse-

quences of attention-driven business models. Several studies suggest that prolonged digital engagement may contribute to reduced productivity, impaired concentration, emotional distress, sleep disturbances, and other adverse outcomes. Twenge and Campbell (2018) found that higher screen time is associated with lower psychological well-being among children and adolescents. These consequences can be interpreted through the economic concepts of negative externalities and information asymmetry, both of which are potential sources of market failure. While digital platforms derive substantial private benefits from increased user engagement, many of the associated social and psychological costs are borne by users and society.

Despite the increasing volume of research on digital technologies and online behaviour, important gaps remain. Much of the existing literature relies on correlational evidence and rarely examines the causal mechanisms linking Digital Access, Asymmetric Information, Screen Use Intensity, Screen Addiction, Productivity Loss, and Mental Health Impact within a unified framework. There is also limited empirical work that examines attention-driven digital markets through the combined lens of behavioural economics, information asymmetry, and market failure.

This chapter reviews the relevant theories and empirical studies relating to the Attention Economy, digital engagement, information asymmetry, negative externalities, and market failure. The insights derived from this review provide the basis for developing the conceptual framework and hypotheses tested in subsequent chapters using Partial Least Squares Structural Equation Modelling (PLS-SEM).

2.2 Theoretical Foundations

The theoretical foundation of the present study is built upon four major perspectives: Attention Scarcity Theory, Attention Economy Theory, the Attention Merchants Framework, and Surveillance Capitalism. Together, these perspectives explain how attention becomes scarce, how it acquires economic value, how digital platforms capture and monetize it, and how informational imbalances arise between platforms and users.

2.2.1 Herbert Simon's Theory of Attention Scarcity

The theoretical roots of the Attention Economy can be traced to Simon (1971), who argued that in an information-rich world, the scarce resource is no longer information itself but the attention required to process it. As technological development increases the volume and accessibility of information, individuals face greater difficulty in selecting, processing, and responding to relevant information. Since human cognitive capacity and time are limited, attention becomes an essential economic resource.

Simon (1971) challenged the traditional economic focus on material scarcity by emphasizing the scarcity of cognitive capacity. His argument is particularly relevant in contemporary digital markets, where users are continuously exposed to notifications, advertisements, algorithmic recommendations, and platform-generated content. In such an environment, platforms compete not merely to provide information but to secure sustained user attention.

In the context of the present study, Simon's theory provides the basic rationale for examining how Digital Access may increase Screen Use Intensity and Screen Addiction. As users gain greater access to digital platforms, they become more exposed to attention-capturing mechanisms that compete for their limited cognitive resources.

2.2.2 Goldhaber's Attention Economy Theory

Goldhaber (1997) extended Simon's idea by arguing that attention functions as a form of currency in the Information Age. When information becomes abundant, economic value increasingly shifts from the production of information to the ability to attract and retain attention. In this sense, attention becomes a scarce and valuable asset that individuals, firms, and digital platforms compete to acquire.

Goldhaber's theory is especially relevant to social media and digital platform markets, where visibility, engagement, and influence are measured through indicators such as views, likes, shares, comments, and watch time. These metrics reflect the extent to which user attention has been captured and converted into economic value. Advertising-based digital platforms are particularly dependent on this process because revenue generation is closely linked to user engagement.

For the present study, Goldhaber's theory supports the argument that user attention is not merely a behavioural outcome but an economic resource. This provides the basis for examining whether attention-driven digital markets generate social costs in the form of Productivity Loss and Mental Health Impact.

2.2.3 Tim Wu's Attention Merchants Framework

Wu (2016) developed the Attention Merchants Framework to explain how media and digital firms construct business models around the capture and sale of human attention. According to Wu (2016), digital platforms operate as attention merchants because their profitability depends on attracting users, retaining their engagement, and selling access to that attention to advertisers.

This framework is useful for understanding the design logic of contemporary platforms. Features such as personalized recommendations, autoplay, push notifications, infinite scrolling, and algorithmically curated feeds are not neutral technological tools. They are engagement mechanisms designed to extend platform use and increase opportunities for advertising exposure. The longer users remain engaged, the greater the commercial value generated for the platform.

In relation to the present study, Wu's framework explains how platform incentives may contribute to Screen Use Intensity and Screen Addiction. It also supports the broader market failure argument, since the private gains of platforms may be accompanied by social costs borne by users in the form of reduced productivity and adverse mental health outcomes.

2.2.4 Surveillance Capitalism

Zuboff (2019) introduced the concept of Surveillance Capitalism to describe how digital platforms generate economic value through the extraction, analysis, and commercialization of behavioural data. Under this model, users' online activities generate behavioural data that are used to predict, influence, and monetize future behaviour.

A central feature of Surveillance Capitalism is the extraction of behavioural surplus. This refers to data generated through online actions such as clicks, searches, browsing patterns, likes, comments, and viewing behaviour. Platforms use this information to improve prediction systems, personalize content, and optimize engagement strategies. As a result, user attention is not only captured but also analysed and shaped through algorithmic systems.

Zuboff (2019) further highlights the existence of information asymmetry in digital markets. Platforms possess extensive knowledge of data collection practices, algorithmic operations, and behavioural prediction systems, while users often have limited awareness of how their actions are monitored and monetized. This informational imbalance is central to the present study because it provides the theoretical foundation for Asymmetric Information as a construct influencing Screen Use Intensity and Screen Addiction.

2.2.5 Theoretical Foundations

Taken together, these theories provide a comprehensive foundation for the present study. Simon (1971) explains why attention becomes scarce in information-rich environments. Goldhaber (1997) explains how attention becomes an economic asset. Wu (2016) explains how digital platforms capture and monetize attention through engagement-driven business models. Zuboff (2019) explains how behavioural data extraction and information asymmetry reinforce attention-based platform power.

These theoretical perspectives collectively support the conceptual framework of this study. They explain why Digital Access may increase Screen Use Intensity and Screen Addiction, why Asymmetric Information may shape user engagement, and why Productivity Loss and Mental Health Impact may be understood as negative externalities generated by attention-driven digital markets.

2.3 Attention Economy and Digital Platforms

The theoretical perspectives discussed in the previous section explain why attention has emerged as a scarce and economically valuable resource in contemporary digital markets. Building upon these foundations, it is necessary to examine how digital platforms operationalize the monetization of attention through specific business models and engagement strategies. Digital platforms do not merely facilitate information exchange; rather, they actively compete for user attention and convert engagement into economic value through advertising, data monetization, and algorithmic optimization. Consequently, understanding platform business models and attention-capture mechanisms is essential for explaining how digital engagement may generate broader behavioural and

economic outcomes.

This section examines the economic foundations of digital platform business models and the algorithmic systems through which user attention is captured, retained, and monetized. Particular attention is given to the role of engagement metrics, behavioural data collection, recommendation systems, and persuasive technologies in shaping user behaviour. These mechanisms provide an important theoretical basis for understanding Screen Use Intensity, Screen Addiction, Productivity Loss, and Mental Health Impact within the Attention Economy.

2.3.1 Platform Business Models

The growth of digital platforms has fundamentally transformed the structure of modern markets and the mechanisms through which economic value is generated. Unlike traditional business models that rely primarily on the sale of goods and services, digital platforms function as intermediaries that connect users, advertisers, content creators, and businesses within a shared digital ecosystem. In these environments, user attention has emerged as a critical economic resource and a key determinant of platform success (Goldhaber, 1997; Wu, 2016).

Social media platforms such as Facebook, Instagram, TikTok, and X (formerly Twitter) exemplify attention-based business models. These platforms typically provide services free of monetary charge to users while generating revenue through advertising and data-driven marketing activities. Their profitability depends on attracting large numbers of users and maximizing engagement levels, as increased interaction creates more opportunities for advertising exposure and behavioural data collection (Wu, 2016; Zuboff, 2019).

Search engines such as Google similarly operate within an attention-driven framework. By organizing information and delivering highly relevant search results, they attract user attention and generate revenue through advertising systems that target users based on their interests, preferences, and online behaviour. The effectiveness of these models depends largely on the platform's ability to retain users and facilitate interactions between advertisers and consumers (Wu, 2016).

Streaming platforms such as YouTube, Netflix, and Spotify also compete intensely for user attention. Whether operating through subscription-based models, advertising-supported models, or hybrid approaches, these platforms rely heavily on sustained engagement. The longer users remain active on the platform, the greater the opportunities for content consumption, data generation, and revenue creation (Goldhaber, 1997; Wu, 2016).

The economic value generated by digital platforms is derived primarily through advertising, data monetization, and user engagement. Advertising remains the dominant source of revenue for many platforms, where user attention is transformed into a marketable commodity and sold to advertisers seeking access to targeted audiences. Consequently, platform revenues are closely linked to the quantity and quality of attention captured and retained (Wu, 2016).

In addition to advertising, digital platforms derive substantial value from the collection and analysis of behavioural data generated through user interactions. These data

enable firms to personalize content, improve advertising effectiveness, and develop predictive models of consumer behaviour, thereby enhancing both user engagement and commercial profitability (Zuboff, 2019). Furthermore, engagement indicators such as watch time, click-through rates, likes, shares, comments, and session duration serve as critical performance metrics because they directly influence advertising outcomes, platform valuation, and revenue generation (Goldhaber, 1997).

Consequently, contemporary digital platforms operate within an economic environment where attention functions as a scarce and valuable resource. Their business models are fundamentally dependent upon attracting, retaining, and monetizing user engagement through advertising, behavioural analytics, and personalized content delivery. While these strategies generate substantial economic value, they may also create incentives for excessive engagement and prolonged screen use. This divergence between platform incentives and user welfare forms an important basis for examining the Attention Economy from the perspective of market failure.

2.3.2 Algorithmic Attention Capture

As competition for user attention has intensified, digital platforms have increasingly adopted algorithmic systems designed to attract, retain, and influence user behaviour. Algorithms determine the visibility of content, prioritize information, and personalize user experiences in ways that maximize engagement and prolong interaction with digital platforms (Zuboff, 2019).

One of the most widely used engagement mechanisms is infinite scrolling. This design feature eliminates natural stopping points by continuously presenting new content as users navigate digital feeds. By reducing opportunities for conscious disengagement, infinite scrolling encourages prolonged usage and increases attention retention (Alter, 2017).

Another commonly employed strategy is autoplay functionality, particularly on video-sharing and streaming platforms. Autoplay automatically initiates subsequent content without requiring user action, thereby extending viewing sessions and increasing overall screen time. This mechanism reduces decision-making effort and encourages continuous content consumption (Alter, 2017).

Personalized feeds represent another powerful tool of attention capture. Through machine learning algorithms and behavioural analytics, platforms identify user preferences and curate content that is most likely to generate engagement. Personalized recommendations increase the relevance of content presented to users, making disengagement less likely and reinforcing habitual platform usage (Pariser, 2011; Zuboff, 2019).

Similarly, push notifications are strategically designed to recapture user attention by prompting users to return to digital platforms. Notifications frequently incorporate elements of urgency, novelty, and social interaction, encouraging immediate responses and repeated platform visits (Fogg, 2003).

The effectiveness of these mechanisms can be understood through the framework of persuasive technology. Fogg (2003) argued that digital technologies can be deliberately designed to influence human behaviour by increasing motivation, simplifying

actions, and providing timely prompts. According to the Fogg Behaviour Model, behaviour occurs when motivation, ability, and triggers converge simultaneously. Many engagement features employed by digital platforms operate according to these principles, encouraging users to interact more frequently and for longer periods.

From a behavioural-economic perspective, these mechanisms exploit predictable cognitive biases and behavioural tendencies. Variable rewards, social validation, personalization, and continuous content availability encourage repeated engagement and reduce the likelihood of disengagement. Consequently, algorithmic systems not only influence how users allocate attention but also shape behavioural patterns that may become habitual over time.

Wu (2016) describes digital firms as "attention merchants" whose business models depend on capturing and selling human attention. From this perspective, algorithmic systems function as tools for maximizing engagement and increasing opportunities for advertising exposure. Zuboff (2019) further argues that these systems not only capture attention but also generate behavioural data that can be used to predict and influence future user actions. Since platforms possess significantly greater information regarding user behaviour and algorithmic operations than users themselves, algorithmic attention capture also contributes to information asymmetry within digital markets.

Therefore, algorithmic attention capture represents both a technological and an economic process through which user engagement is transformed into commercial value. Through continuous personalization, behavioural reinforcement, and predictive optimization, digital platforms seek to maximize user attention and increase opportunities for monetization. These mechanisms may increase Screen Use Intensity and contribute to the development of Screen Addiction by encouraging repeated and prolonged engagement with digital environments. Consequently, algorithmic attention capture provides an important theoretical link between platform business models and the behavioural outcomes examined in the present study, including Productivity Loss and Mental Health Impact.

2.3.3 Bounded Rationality

Behavioural economics challenges the traditional economic assumption that individuals consistently behave as fully rational decision-makers capable of processing all available information and selecting utility-maximizing choices. One of the most influential contributions in this field is Herbert Simon's theory of bounded rationality, which argues that decision-making is constrained by limited cognitive resources, incomplete information, and finite time (Simon, 1955; Simon, 1957). Under such conditions, individuals are unable to evaluate all available alternatives and therefore rely on simplified decision-making strategies or heuristics.

According to Simon (1957), individuals operate under conditions of cognitive scarcity, where their capacity to process information is substantially lower than the amount of information available to them. Rather than pursuing optimal solutions, individuals frequently engage in a process of "satisficing," whereby decisions are based on outcomes that are satisfactory rather than objectively optimal. This perspective departs from conventional economic models of perfect rationality and provides a more realistic ex-

planation of decision-making behaviour in complex environments.

The concept of bounded rationality is particularly relevant in contemporary digital environments, where individuals are continuously exposed to vast quantities of information, notifications, advertisements, recommendations, and multimedia content. The rapid expansion of digital technologies has increased the volume and speed of information flows beyond the cognitive capacity of most users. As a result, users often rely on heuristics, habitual behaviours, and platform-generated cues when making decisions regarding content consumption and digital engagement.

Within the Attention Economy, bounded rationality provides an important explanation for why users may struggle to allocate attention efficiently. Digital platforms compete intensely for users' limited cognitive resources through engagement-enhancing features such as personalized recommendations, autoplay functions, push notifications, and infinite scrolling interfaces. Simon (1971) argued that while information may be abundant, attention remains scarce. Consequently, users operating under conditions of bounded rationality may experience cognitive overload and reduced capacity for self-regulation, making them more susceptible to persuasive platform designs.

Behavioural economists have further argued that individuals frequently underestimate the long-term consequences of present decisions when faced with immediate rewards and continuous stimulation. In digital environments, immediate gratifications associated with social interaction, entertainment, novelty, and personalized content may encourage repeated engagement even when such behaviour conflicts with long-term goals relating to productivity, well-being, or time management. As a result, users may allocate excessive amounts of time and attention to digital platforms despite recognizing potential adverse consequences.

From the perspective of the present study, bounded rationality provides an important theoretical explanation for the relationships between Digital Access, Screen Use Intensity, and Screen Addiction. Greater Digital Access increases exposure to attention-capturing digital environments, while cognitive limitations reduce users' ability to fully evaluate and regulate their engagement. Consequently, prolonged exposure may contribute to higher levels of Screen Use Intensity and increase the likelihood of Screen Addiction. These behavioural outcomes may subsequently generate Productivity Loss and Mental Health Impact, thereby contributing to the broader social costs associated with the Attention Economy.

Thus, bounded rationality highlights how cognitive limitations can influence digital behaviour and supports the argument that attention-driven digital markets may produce outcomes that deviate from socially optimal levels of engagement. The theory therefore provides an important behavioural-economic foundation for understanding the mechanisms through which the Attention Economy may contribute to negative externalities and market failure.

2.3.4 Behavioural Manipulation

Behavioural manipulation refers to the deliberate use of psychological principles, behavioural insights, and environmental cues to influence individual decision-making and behaviour. Behavioural economics has demonstrated that individuals do not al-

ways make decisions through fully rational evaluation. Instead, choices are often shaped by cognitive biases, heuristics, emotions, and contextual influences. Digital platforms increasingly incorporate these behavioural insights into platform design to encourage greater engagement, increase user retention, and maximize attention capture (Fogg, 2003).

One of the most influential concepts in behavioural economics is the notion of a *nudge*, introduced by Thaler and Sunstein (2008). A nudge refers to any aspect of choice architecture that predictably alters behaviour without restricting freedom of choice or significantly changing economic incentives. Rather than eliminating alternatives, nudges influence decision-making by making certain actions more salient, convenient, or attractive.

The application of these principles within digital environments has given rise to the concept of *digital nudging*. Weinmann et al. (2016) define digital nudging as the use of user-interface design, algorithms, notifications, and personalized recommendations to guide behaviour in online environments. Examples include reminders encouraging users to revisit applications, notifications highlighting social interactions, personalized content recommendations, and prompts designed to increase user engagement. Although these interventions preserve user choice, they can substantially influence behavioural outcomes.

A closely related concept is *choice architecture*, which refers to the manner in which choices are structured and presented to individuals (Thaler & Sunstein, 2008). In digital markets, platforms carefully design interfaces to reduce friction, increase convenience, and encourage habitual behaviour. Features such as infinite scrolling, autoplay functionality, personalized feeds, streak mechanisms, and push notifications are examples of digital choice architectures intended to shape user decisions and increase engagement.

The behavioural effects of these mechanisms can be further understood through Fogg's Behaviour Model. According to Fogg (2009), behaviour occurs when three elements converge simultaneously: motivation, ability, and a trigger. Digital platforms frequently employ design features that increase motivation through social rewards and personalized content, enhance ability by simplifying user actions, and provide continuous triggers through notifications and recommendations. Consequently, engagement becomes easier, more rewarding, and more likely to occur repeatedly.

From a behavioural-economic perspective, these practices extend beyond simple user-interface design. They represent systematic attempts to influence attention allocation and behavioural outcomes. By exploiting cognitive biases such as present bias, social validation, loss aversion, and reward-seeking behaviour, digital platforms can increase the frequency and duration of user engagement. As a result, users may allocate greater amounts of time and attention to digital activities than they would under conditions of complete information and fully rational decision-making.

Within the Attention Economy, behavioural manipulation functions as a key mechanism through which platforms capture and retain user attention. By strategically employing digital nudges, persuasive technologies, and behavioural design principles, platforms align user behaviour with commercial objectives centred on engagement and monetization (Wu, 2016). These mechanisms are particularly relevant to the present

study because they provide a behavioural explanation for how increased Digital Access may contribute to higher levels of Screen Use Intensity and facilitate the development of Screen Addiction.

Moreover, behavioural manipulation highlights the potential role of information asymmetry in digital markets. While platforms possess extensive knowledge regarding behavioural design techniques and engagement optimization strategies, users often remain unaware of the psychological mechanisms influencing their decisions. This informational imbalance may limit users' ability to make fully informed choices regarding their digital engagement. Consequently, behavioural manipulation provides an important link between platform incentives, user behaviour, and the broader market failure framework that underpins the present study.

2.3.5 Information Asymmetry

Information asymmetry is a fundamental concept in economics that describes situations in which one party possesses significantly more information than another during an economic transaction. The concept was formally introduced by Akerlof (1970) in his seminal work *The Market for "Lemons"*, which demonstrated how unequal access to information can generate inefficient market outcomes, distort decision-making, and reduce social welfare. Since then, information asymmetry has become a central explanation for various forms of market failure across economic contexts.

The relevance of information asymmetry has increased considerably in the digital economy. Unlike traditional markets, digital platforms collect vast quantities of behavioural data relating to user preferences, browsing patterns, online interactions, purchasing behaviour, and attention allocation. Through sophisticated algorithms, machine learning systems, and predictive analytics, platforms transform these data into valuable insights that enable them to influence content visibility, personalize recommendations, and optimize user engagement. Users, however, often possess only limited knowledge regarding how these processes operate (Zuboff, 2019).

This informational imbalance creates a situation in which platform operators possess substantially greater knowledge regarding engagement mechanisms, recommendation algorithms, behavioural prediction systems, and monetization strategies than the users interacting with these platforms. Although users voluntarily participate in digital ecosystems, they frequently lack detailed information concerning how their attention is captured, analysed, and monetized. Consequently, users may underestimate the extent to which platform architectures influence their behaviour and attention allocation (Zuboff, 2019).

Within the Attention Economy, information asymmetry assumes particular significance because attention itself has become an economically valuable resource. Platforms continuously collect behavioural information and utilize these insights to refine engagement-maximizing strategies. Personalized feeds, targeted advertisements, recommendation systems, autoplay features, and notification mechanisms are developed using information that is largely unavailable to users. As a result, users often make decisions under conditions of incomplete information, while platforms operate with extensive knowledge regarding behavioural responses and engagement patterns.

From a behavioural-economic perspective, information asymmetry may increase users' susceptibility to persuasive platform designs and engagement-enhancing mechanisms. When individuals lack sufficient knowledge regarding algorithmic processes and behavioural targeting practices, they may be less capable of evaluating the long-term consequences of their digital engagement. Consequently, information asymmetry may contribute to higher levels of Screen Use Intensity and increase the likelihood of Screen Addiction by reducing users' ability to make fully informed decisions regarding their digital behaviour.

The concept also provides an important explanation for market failure within digital markets. Economic theory suggests that efficient market outcomes require participants to possess adequate information when making decisions. When information is distributed unevenly, decision-making may become inefficient and welfare outcomes may deteriorate. Stiglitz (2000) argued that information imperfections represent one of the most significant sources of market failure because they prevent individuals from making optimal choices. In attention-driven digital markets, the unequal distribution of information between platforms and users may therefore contribute to excessive engagement, behavioural dependency, and broader social costs.

In the context of the present study, Information Asymmetry provides the theoretical foundation for the construct Asymmetric Information (AS). The theory suggests that unequal access to information may directly influence Screen Use Intensity and Screen Addiction while also shaping the relationship between Digital Access and digital engagement outcomes. Users with limited awareness of platform practices may be more vulnerable to attention-capturing mechanisms, thereby strengthening the behavioural effects associated with the Attention Economy. Consequently, information asymmetry constitutes a key mechanism through which attention-driven digital markets may generate negative externalities and contribute to market failure.

2.3.6 Concept of Screen Use Intensity

The rapid diffusion of digital technologies has significantly increased the amount of time individuals spend interacting with screens. Smartphones, tablets, computers, and other digital devices have become integral components of everyday life, facilitating communication, entertainment, education, commerce, and professional activities. As digital technologies become increasingly embedded within daily routines, Screen Use Intensity has emerged as an important construct for understanding contemporary patterns of digital behaviour.

Screen Use Intensity generally refers to the frequency, duration, and level of engagement associated with the use of digital devices and online platforms (Twenge & Campbell, 2018). It encompasses not only the amount of time individuals spend using screens but also the extent to which they interact with digital content, applications, and online environments. Higher levels of Screen Use Intensity often reflect increased engagement with social media platforms, streaming services, online gaming, digital communication tools, and other forms of internet-based activity.

One important dimension of Screen Use Intensity is daily screen exposure. Research indicates that the average amount of time individuals spend interacting with

digital devices has increased substantially over the past decade, particularly among adolescents and young adults (Twenge & Campbell, 2018). Prolonged screen exposure has been associated with a range of behavioural and psychological outcomes, including reduced attention span, sleep disturbances, and diminished well-being (Kross et al., 2013). Although screen engagement can facilitate learning, communication, and productivity, excessive exposure may create challenges for effective attention allocation and self-regulation.

Another important dimension is social media engagement. Social media platforms encourage users to browse content, share information, interact with peers, and consume user-generated media. Through personalized content feeds, social feedback mechanisms, and continuous content updates, these platforms are specifically designed to encourage repeated interaction and sustained engagement (Andreassen, 2015). Consequently, users may devote substantial amounts of time and attention to social networking activities.

A related aspect of Screen Use Intensity is smartphone dependence. Smartphones provide continuous access to digital platforms and online services, making them a primary gateway to the Attention Economy. Their portability, accessibility, and multifunctionality allow users to remain connected throughout the day. Kwon et al. (2013) found that excessive reliance on smartphones is associated with increased screen exposure, reduced self-regulation, and problematic patterns of technology use.

From the perspective of the Attention Economy, Screen Use Intensity represents a behavioural manifestation of attention allocation within digital environments. Digital platforms compete continuously for user attention through notifications, personalized recommendations, social interaction features, and algorithmically curated content. As individuals allocate increasing amounts of time and cognitive resources to these environments, Screen Use Intensity becomes an indicator of the extent to which attention has been captured and retained by digital platforms.

Within the context of the present study, Screen Use Intensity represents an important behavioural outcome of Digital Access and Asymmetric Information. It also serves as a potential mechanism through which attention-driven digital environments may influence Productivity Loss and Mental Health Impact. While high levels of Screen Use Intensity do not necessarily imply addictive behaviour, prolonged and intensive engagement may increase vulnerability to the development of Screen Addiction. Consequently, understanding Screen Use Intensity is essential for analysing the behavioural and economic implications of the Attention Economy.

2.3.7 Screen Addiction

As digital technologies become increasingly embedded in everyday life, concerns have emerged regarding the development of compulsive and maladaptive patterns of digital engagement. While Screen Use Intensity reflects the frequency and duration of digital device usage, Screen Addiction refers to a more severe behavioural condition characterized by excessive and uncontrolled engagement with digital technologies despite awareness of adverse consequences. Kuss and Griffiths (2017) argued that screen addiction involves persistent behavioural dependence that interferes with personal, social,

academic, and professional functioning. Consequently, screen addiction represents not merely high levels of usage but a loss of behavioural control over digital consumption.

One of the most extensively studied forms of digital addiction is smartphone addiction. Smartphone addiction is characterized by excessive device usage, withdrawal symptoms when access is restricted, difficulty regulating usage behaviour, and continued engagement despite negative outcomes. Kwon et al. (2013) found that smartphones possess unique addictive characteristics because they provide constant access to communication, entertainment, information, and social interaction. Their portability and continuous availability further increase opportunities for compulsive engagement.

Another closely related construct is social media addiction, which refers to excessive involvement in social networking platforms. Individuals exhibiting social media addiction often engage in compulsive checking behaviours, experience emotional dependence on online interactions, and encounter difficulties reducing platform usage despite recognizing its negative effects. Andreassen (2015) observed that social validation mechanisms such as likes, comments, shares, and follower counts provide continuous psychological reinforcement, encouraging repeated engagement and increasing the risk of dependency.

Similarly, internet addiction refers to problematic and uncontrolled internet use that interferes with normal daily functioning. Young (1998) was among the first researchers to conceptualize internet addiction as a behavioural disorder characterized by excessive online engagement, impaired self-regulation, and negative life consequences. Subsequent research has demonstrated that various forms of digital engagement share common behavioural and psychological characteristics associated with addiction.

The theoretical foundation for understanding these phenomena can be found in Behavioural Addiction Theory. Griffiths (2005) argued that behavioural addictions share many characteristics with substance-based addictions, including salience, mood modification, tolerance, withdrawal symptoms, conflict, and relapse. Unlike substance addictions, behavioural addictions arise from compulsive engagement in rewarding activities rather than the consumption of psychoactive substances. Digital technologies can become behaviourally addictive because they provide immediate rewards, social reinforcement, and continuous opportunities for engagement.

Another important theoretical perspective is Reinforcement Theory. Skinner (1953) proposed that behaviours become more likely to occur when followed by rewarding outcomes. Digital platforms continuously provide users with social feedback, entertainment, novelty, and informational rewards. These positive reinforcements strengthen engagement patterns and increase the likelihood of repeated platform usage.

Closely related to reinforcement processes are variable reward mechanisms, which occur when rewards are delivered unpredictably rather than consistently. Alter (2017) argued that variable reward schedules are particularly effective in maintaining behavioural engagement because individuals continue seeking rewards despite uncertainty regarding when they will occur. Notifications, likes, comments, messages, and personalized recommendations frequently operate according to this principle, creating powerful incentives for repeated engagement and prolonged platform usage.

Within the Attention Economy, Screen Addiction represents a critical behavioural outcome of sustained exposure to attention-capturing digital environments. Algorith-

mically curated content, persuasive technologies, personalized recommendations, and continuous social feedback mechanisms may gradually transform routine digital engagement into compulsive behavioural patterns. As a result, individuals may continue allocating substantial amounts of time and attention to digital platforms even when such behaviour conflicts with personal goals, productivity requirements, or psychological well-being.

From the perspective of the present study, Screen Addiction serves as a key mechanism through which Digital Access and Asymmetric Information may generate broader behavioural and welfare consequences. Excessive and compulsive digital engagement may reduce productivity, impair concentration, disrupt daily activities, and negatively affect mental health. Consequently, Screen Addiction occupies a central position within the conceptual framework of the study and provides an important pathway through which the Attention Economy may contribute to negative externalities and market failure.

2.3.8 Digital Addiction Mechanisms

The addictive potential of digital platforms can be better understood through the psychological, behavioural, and neurological mechanisms that underpin user engagement. Contemporary research increasingly emphasizes the role of reward systems, habit formation processes, behavioural reinforcement, and cognitive biases in explaining the development of digital addiction. These mechanisms help explain why routine digital engagement may gradually evolve into compulsive patterns of behaviour.

One important mechanism involves dopamine-mediated reward processes. Dopamine is a neurotransmitter associated with reward anticipation, motivation, learning, and reinforcement. Montag and Walla (2016) argued that digital interactions generating social approval, novelty, achievement, or anticipated rewards can stimulate dopamine activity, creating positive reinforcement that encourages repeated engagement. Over time, users may develop strong behavioural associations between platform usage and rewarding experiences, making disengagement increasingly difficult.

Habit formation represents another important mechanism underlying digital addiction. Repeated exposure to notifications, personalized content, and social feedback gradually transforms intentional behaviour into automatic routines. According to Wood and Neal (2007), habits develop when behaviours are repeatedly performed in stable contexts, eventually becoming automatic responses to environmental cues. As engagement becomes habitual, users may interact with digital platforms with limited conscious deliberation, increasing the likelihood of compulsive usage patterns.

Variable reward schedules further strengthen addictive behaviour. Unlike predictable rewards, variable rewards occur intermittently and unpredictably, encouraging users to continue seeking future rewards despite uncertainty regarding when they will occur. Alter (2017) noted that social media notifications, content recommendations, messages, and online interactions frequently operate through such mechanisms, reinforcing continued engagement and increasing behavioural persistence. Because rewards are delivered unpredictably, users are motivated to check platforms repeatedly in anticipation of future rewards.

Another important factor is the Fear of Missing Out (FOMO), which refers to the apprehension that others may be experiencing rewarding activities from which one is absent. Przybylski et al. (2013) found that FOMO is strongly associated with excessive social media use and problematic smartphone behaviour because it motivates individuals to remain continuously connected and monitor digital interactions. The desire to avoid missing social information can therefore encourage frequent platform checking and prolonged engagement.

Social validation mechanisms also contribute significantly to digital addiction. Features such as likes, comments, shares, follower counts, and online recognition provide immediate feedback regarding social acceptance and approval. Andreassen (2015) observed that such mechanisms encourage users to seek repeated social reinforcement, thereby strengthening engagement patterns and increasing dependence on digital interactions.

From a behavioural-economic perspective, these mechanisms exploit predictable cognitive biases and behavioural tendencies. Immediate rewards often receive greater weight than long-term consequences, causing individuals to prioritize short-term gratification over future well-being. Consequently, users may continue engaging with digital platforms even when such behaviour conflicts with productivity goals, academic responsibilities, or psychological health.

Collectively, these mechanisms illustrate how digital platforms can transform ordinary engagement into persistent and compulsive behavioural patterns. Through a combination of neurological rewards, behavioural reinforcement, habit formation, and psychological motivations, attention-driven digital environments increase the likelihood of Screen Addiction. These mechanisms provide an important theoretical explanation for the behavioural pathways examined in the present study and help explain how Digital Access and Asymmetric Information may ultimately contribute to Productivity Loss and Mental Health Impact through addictive patterns of digital engagement.

2.4 Attention Economy and Mental Health

The rapid expansion of digital technologies and attention-driven platforms has generated growing concern regarding their implications for mental health and psychological well-being. As social media platforms, streaming services, gaming applications, and other digital technologies increasingly compete for user attention, researchers have devoted considerable attention to understanding their psychological consequences. Particular concern has been expressed regarding outcomes such as anxiety, depression, loneliness, sleep disruption, emotional exhaustion, and reduced subjective well-being, which are frequently associated with intensive digital engagement (Twenge and Campbell, 2018; Kross et al., 2013).

Within the Attention Economy, user engagement is actively encouraged through personalized content, social feedback mechanisms, algorithmic recommendations, and continuous streams of information. While these features enhance connectivity and access to information, they may also increase psychological vulnerability by encouraging excessive digital engagement and prolonged exposure to attention-capturing stimuli. Consequently, mental health has emerged as an important dimension for evaluating the

broader welfare implications of attention-driven digital markets.

2.4.1 Anxiety and Depression

Anxiety and depression are among the most extensively studied psychological outcomes associated with excessive digital engagement. A growing body of literature suggests that prolonged exposure to social media and other digital platforms may contribute to psychological distress through mechanisms such as social comparison, Fear of Missing Out (FOMO), cyberbullying, information overload, and continuous exposure to idealized representations of others' lives (Primack et al., 2017).

Twenge and Campbell (2018) reported significant associations between increased screen time and lower psychological well-being among children and adolescents. Their findings indicated that individuals with higher levels of screen exposure were more likely to report symptoms associated with anxiety, depression, emotional distress, and reduced life satisfaction. Similarly, Kross et al. (2013) found that increased Facebook usage predicted declines in subjective well-being over time, suggesting that greater engagement with social media may negatively affect emotional health.

One explanation for these outcomes lies in the process of social comparison. Social media platforms frequently expose users to carefully curated representations of success, attractiveness, and achievement. Repeated exposure to such content may encourage individuals to evaluate themselves unfavourably relative to others, thereby increasing feelings of inadequacy, anxiety, and depressive symptoms. In addition, the constant availability of social information may generate concerns regarding social exclusion and missed experiences, further contributing to psychological distress.

From the perspective of the Attention Economy, these outcomes can be interpreted as unintended consequences of engagement-maximizing platform designs. Digital platforms benefit economically from prolonged user engagement, yet the psychological costs associated with excessive usage may be borne primarily by users. This divergence between private platform incentives and individual welfare highlights the relevance of mental health concerns within broader discussions of market failure and negative externalities.

However, the empirical evidence is not entirely uniform. Orben and Przybylski (2019) argued that although statistically significant relationships often exist between digital technology use and mental health outcomes, the magnitude of these effects is generally modest. Their findings suggest that screen exposure alone may not fully explain variations in psychological well-being and that individual characteristics, social environments, and patterns of platform use should also be considered.

Nevertheless, the existing literature broadly indicates that excessive and uncontrolled engagement with digital platforms may increase the risk of anxiety and depression, particularly when digital usage evolves into compulsive or addictive behavioural patterns. These findings are highly relevant to the present study because they support the proposition that Screen Addiction may contribute to adverse Mental Health Impact within attention-driven digital environments.

2.4.2 Loneliness and Social Isolation

Digital platforms are frequently promoted as tools that enhance communication, connectivity, and social interaction. Through social networking sites, messaging applications, and online communities, individuals can maintain relationships, exchange information, and interact with others regardless of geographical distance. Despite these benefits, researchers have increasingly questioned whether greater online connectivity necessarily translates into meaningful social relationships and improved psychological well-being.

A growing body of literature suggests that excessive engagement with social media may contribute to feelings of loneliness and perceived social isolation despite increasing opportunities for virtual communication. Primack et al. (2017) found that individuals with higher levels of social media use were significantly more likely to experience perceived social isolation. Their findings indicate that greater online engagement does not always correspond to stronger social connectedness and may, in some cases, intensify feelings of social disconnection.

One explanation for this relationship is that online interactions may sometimes substitute for rather than complement face-to-face social relationships. While digital communication enables frequent contact, it may not provide the same emotional depth, trust, and social support associated with direct interpersonal interaction. Consequently, individuals may remain socially connected in a technical sense while simultaneously experiencing feelings of loneliness and emotional isolation.

Another important mechanism involves social comparison. Social media platforms expose users to carefully curated representations of others' lives, achievements, and experiences. Vogel et al. (2014) argued that repeated exposure to idealized content may encourage individuals to engage in upward social comparison, resulting in lower self-esteem, reduced life satisfaction, and greater feelings of loneliness. Passive consumption of social media content appears particularly associated with these outcomes because users compare themselves with others without actively participating in meaningful social interactions.

From the perspective of the Attention Economy, these outcomes may be viewed as unintended consequences of engagement-maximizing platform designs. Social media algorithms prioritize content that generates attention, interaction, and emotional responses. While such mechanisms increase user engagement and platform profitability, they may simultaneously contribute to psychological outcomes that reduce overall well-being. In this sense, feelings of loneliness and social isolation may represent broader social costs associated with attention-driven digital markets.

However, the empirical evidence remains mixed. Verduyn et al. (2017) argued that digital platforms can also strengthen social relationships when used for communication, collaboration, and relationship maintenance. Their findings suggest that the psychological effects of social media depend not only on the amount of usage but also on the manner in which platforms are used. Active engagement, such as direct communication and relationship-building activities, may enhance social connectedness, whereas passive consumption of content may increase feelings of loneliness and isolation.

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Overall, the literature suggests that the relationship between digital engagement and loneliness is complex and context-dependent. While digital platforms have the

potential to strengthen social connections, excessive or passive forms of engagement may contribute to perceived social isolation and reduced psychological well-being. These findings are particularly relevant to the present study because loneliness and social isolation constitute important dimensions of Mental Health Impact that may arise from excessive engagement with attention-driven digital environments.

2.4.3 Sleep Disruption

Sleep disruption is another important consequence associated with excessive digital engagement and has emerged as a growing public health concern in the digital era. Smartphones, social media platforms, streaming services, and online applications enable continuous connectivity, often encouraging individuals to remain active online late into the night. As digital platforms increasingly compete for user attention, concerns have been raised regarding their effects on sleep quality, sleep duration, and overall psychological well-being.

A substantial body of research suggests that prolonged screen exposure, particularly during evening hours, is associated with delayed sleep onset, reduced sleep quality, and shorter sleep duration. Levenson et al. (2017) found that individuals with higher levels of social media use were significantly more likely to experience sleep disturbances and poor sleep quality. These findings indicate that excessive digital engagement may interfere with healthy sleep patterns and contribute to broader psychological difficulties.

The relationship between digital technology use and sleep disruption can be explained through both physiological and behavioural mechanisms. From a physiological perspective, exposure to blue light emitted by digital screens may suppress melatonin production, a hormone that regulates sleep-wake cycles. Reduced melatonin levels can delay sleep onset and disrupt natural circadian rhythms, making it more difficult for individuals to achieve restorative sleep (Levenson et al., 2017).

Behavioural mechanisms also play an important role. Digital platforms frequently provide emotionally stimulating content, social interactions, entertainment, and continuous streams of information that increase cognitive arousal. Notifications, messages, personalized recommendations, and algorithmically curated content may encourage users to remain engaged even when they intend to disengage. Consequently, individuals may postpone sleep in order to continue interacting with digital platforms, thereby reducing total sleep duration.

From the perspective of the Attention Economy, sleep disruption may be viewed as an unintended consequence of engagement-maximizing platform designs. Features such as infinite scrolling, autoplay functionality, personalized feeds, and continuous notifications are designed to prolong user engagement and increase attention retention. While these mechanisms contribute to platform profitability, they may simultaneously interfere with healthy behavioural routines, including adequate sleep. In this sense, sleep disruption represents a potential negative externality arising from attention-driven digital markets.

Research further suggests that poor sleep quality may exacerbate symptoms of anxiety, depression, emotional distress, and reduced psychological well-being. Twenge

and Campbell (2018) reported that individuals experiencing higher levels of screen exposure frequently exhibited lower levels of psychological well-being, partly due to sleep-related difficulties. Consequently, sleep disruption may act as an important pathway through which excessive digital engagement contributes to broader Mental Health Impact.

Overall, the literature indicates that excessive engagement with digital technologies can adversely affect sleep quality through both physiological and behavioural mechanisms. These findings are particularly relevant to the present study because sleep disruption represents an important dimension of Mental Health Impact and provides further evidence regarding the potential social costs associated with attention-driven digital environments.

2.4.4 Emotional Exhaustion

Emotional exhaustion refers to a state of psychological fatigue, mental depletion, and reduced emotional capacity resulting from prolonged exposure to cognitive and emotional demands. It is commonly regarded as a central component of psychological strain and has increasingly been examined in relation to digital technology use and online engagement. Within contemporary digital environments, individuals are continuously exposed to information streams, social interactions, notifications, online obligations, and attention-demanding content that require sustained cognitive processing and emotional investment (Bright et al., 2015).

The emergence of the Attention Economy has intensified these demands by creating digital environments specifically designed to maximize user engagement. Social media platforms, streaming services, messaging applications, and other digital technologies encourage continuous connectivity through personalized recommendations, real-time updates, social feedback mechanisms, and algorithmically curated content. While these features enhance user engagement, they also increase the volume of information and interactions that individuals must process on a daily basis.

Bright et al. (2015) argued that excessive exposure to social media and digital communication channels may contribute to social overload and information overload, both of which are associated with emotional exhaustion. Information overload occurs when the quantity of information exceeds an individual's capacity to process it effectively, while social overload arises when users experience pressure to respond to messages, maintain online relationships, and remain socially available. Together, these conditions can generate stress, fatigue, and reduced psychological well-being.

Frequent interruptions represent another important source of emotional exhaustion. Notifications, messages, emails, and platform alerts repeatedly compete for users' attention, disrupting concentration and increasing cognitive switching costs. Such interruptions require individuals to continuously reallocate attention across multiple tasks and information sources, which may contribute to mental fatigue and diminished emotional resilience over time.

From a behavioural-economic perspective, emotional exhaustion may arise because individuals possess limited cognitive and emotional resources. As digital platforms continuously compete for attention, users may allocate increasing amounts of

mental effort toward online engagement. Over time, this sustained demand on cognitive resources may reduce individuals' capacity for self-regulation, increase stress levels, and contribute to feelings of emotional depletion.

Wu (2016) argued that attention-driven business models rely upon the continuous capture and retention of user attention. Consequently, digital platforms have strong incentives to maximize engagement through design features that encourage repeated interaction and prolonged usage. While such strategies increase platform profitability, they may simultaneously impose psychological costs on users in the form of cognitive overload, stress, and emotional exhaustion.

From an economic perspective, emotional exhaustion can therefore be viewed as a negative externality of attention-driven digital markets. Digital platforms derive private benefits from increased engagement, whereas many of the associated psychological costs are borne by users. This divergence between private incentives and social welfare provides further support for the argument that the Attention Economy may contribute to market failure through unaccounted behavioural and psychological consequences.

Overall, the literature suggests that excessive digital engagement may contribute to emotional exhaustion through information overload, social overload, frequent interruptions, and sustained cognitive demands. These findings are particularly relevant to the present study because emotional exhaustion represents an important dimension of Mental Health Impact and illustrates how attention-driven digital environments may generate broader welfare costs for users.

2.4.5 Evidence from Studies on Screen Time and Mental Health

The relationship between screen time and mental health has received considerable scholarly attention over the past decade. As digital technologies have become increasingly integrated into everyday life, researchers have sought to determine whether prolonged engagement with digital devices contributes to adverse psychological outcomes. Although the empirical literature generally identifies a relationship between intensive digital engagement and mental health concerns, the magnitude and nature of these effects remain subjects of ongoing debate.

Twenge and Campbell (2018) reported that higher levels of screen exposure were associated with lower psychological well-being, reduced happiness, increased emotional difficulties, and a greater likelihood of experiencing mental health problems. Their findings suggest that excessive screen engagement may negatively affect emotional functioning and overall well-being, particularly among younger populations. Similarly, Kross et al. (2013) found that increased Facebook usage predicted declines in subjective well-being over time, indicating that intensive social media engagement may contribute to adverse psychological outcomes.

Additional evidence has linked excessive digital engagement to loneliness, social isolation, and sleep-related difficulties. Primack et al. (2017) observed that individuals with higher levels of social media use were more likely to report perceived social isolation, while Levenson et al. (2017) found significant associations between social media use and sleep disturbance. Since loneliness and poor sleep quality are themselves important predictors of psychological distress, these findings suggest that dig-

ital engagement may indirectly influence mental health through multiple behavioural pathways.

The literature also highlights the role of behavioural addiction in shaping mental health outcomes. Studies examining problematic smartphone use, social media addiction, and compulsive internet use have consistently reported associations with anxiety, depression, emotional exhaustion, and reduced psychological well-being (Andreassen, 2015; Kuss and Griffiths, 2017). These findings suggest that addictive patterns of digital engagement may be more strongly associated with adverse mental health outcomes than screen exposure alone.

Despite these concerns, the empirical evidence is not entirely uniform. Orben and Przybylski (2019) argued that although statistically significant relationships often exist between digital technology use and mental health, the magnitude of these effects is generally modest. Their analysis suggests that screen time alone may explain only a small proportion of variations in psychological well-being. Similarly, Verduyn et al. (2017) contended that the effects of social media depend largely on patterns of use rather than overall usage levels. Active engagement involving communication and relationship maintenance may generate different outcomes from passive browsing and content consumption.

These contrasting findings indicate that the relationship between digital engagement and mental health is complex and influenced by multiple factors. Contemporary research increasingly suggests that the quality, purpose, and intensity of digital engagement may be more important than screen exposure alone. In particular, compulsive and addictive patterns of digital behaviour appear to have stronger and more consistent associations with adverse psychological outcomes than routine or purposeful digital use.

Overall, the literature provides substantial evidence that excessive and uncontrolled engagement with digital technologies may contribute to anxiety, depression, loneliness, sleep disruption, emotional exhaustion, and reduced psychological well-being. At the same time, the mixed nature of empirical findings suggests that mental health outcomes are shaped not only by the quantity of digital engagement but also by the manner in which digital technologies are used. These findings are highly relevant to the present study because they support the proposition that Screen Addiction may serve as a more important determinant of Mental Health Impact than Screen Use Intensity alone.

2.4.6 Inconsistencies in the Literature

Despite the growing body of research examining the relationship between digital technology use and mental health, the empirical evidence remains far from conclusive. While numerous studies report significant associations between excessive digital engagement and adverse psychological outcomes, other studies suggest that these relationships are weaker, more context-dependent, or influenced by additional behavioural and social factors.

Several scholars have reported negative effects of digital engagement on mental health outcomes. Twenge and Campbell (2018) found that higher levels of screen exposure were associated with lower psychological well-being, increased emotional

distress, and greater risks of anxiety and depression. Similarly, Kross et al. (2013) reported that increased Facebook usage predicted declines in subjective well-being, while Primack et al. (2017) observed a significant relationship between social media use and perceived social isolation. Levenson et al. (2017) further identified associations between intensive social media engagement and sleep disturbances, suggesting that prolonged digital interaction may adversely affect psychological health through multiple pathways.

In contrast, other researchers have questioned the magnitude and consistency of these effects. Orben and Przybylski (2019) argued that although statistically significant relationships often exist between digital technology use and mental health outcomes, the observed effect sizes are generally modest. Similarly, Verduyn et al. (2017) emphasized that the consequences of digital engagement depend largely on the nature of platform use rather than usage duration alone. Their findings suggest that active participation involving communication and relationship maintenance may generate different outcomes from passive browsing and content consumption.

These inconsistencies may arise from differences in measurement approaches, sample characteristics, research designs, and conceptual definitions. Many studies rely on self-reported measures of screen time, which may be subject to recall errors and reporting bias. Furthermore, the concept of screen exposure itself is multidimensional, encompassing a wide range of activities including social networking, entertainment, education, gaming, and professional work. Consequently, aggregate measures of screen time may fail to capture important differences in the quality and purpose of digital engagement.

Another limitation of the existing literature is its predominant reliance on correlational research designs. Although many studies identify associations between digital engagement and mental health outcomes, relatively few examine the underlying behavioural mechanisms through which these relationships operate. In particular, limited attention has been devoted to understanding how Digital Access influences Screen Use Intensity and Screen Addiction, and how these behavioural outcomes subsequently affect mental health and well-being.

Moreover, the role of information asymmetry has received comparatively little empirical attention. While digital platforms possess extensive knowledge regarding user behaviour, algorithmic systems, and engagement optimization strategies, users often have limited awareness of how their attention is captured, analysed, and monetized. The extent to which such informational imbalances influence behavioural outcomes remains insufficiently explored within the existing literature.

Finally, much of the empirical evidence originates from developed economies, particularly the United States and Europe. Although digital adoption has expanded rapidly across emerging economies, relatively few studies have examined the behavioural and psychological implications of the Attention Economy within rapidly growing digital environments. This limits the generalizability of existing findings and highlights the need for further research in diverse socio-economic contexts.

In view of these limitations, there remains a need for comprehensive research that examines the direct, indirect, and moderating relationships among Digital Access, Screen Use Intensity, Screen Addiction, Mental Health Impact, and Asymmetric In-

formation within a unified analytical framework. The present study seeks to address these gaps through the application of Partial Least Squares Structural Equation Modelling (PLS-SEM), thereby providing deeper insights into the behavioural and economic consequences of the Attention Economy. "'latex

2.5 Attention Economy and Productivity Loss

Productivity is generally defined as the efficiency with which individuals utilize available resources, including time, effort, attention, and cognitive capacity, to achieve desired outcomes. In knowledge-based economies, productivity depends not only on physical effort but also on an individual's ability to concentrate, process information, make decisions, and sustain attention on goal-oriented activities. Consequently, attention has increasingly been recognized as a critical economic resource influencing individual and organizational performance.

The emergence of the Attention Economy has generated growing concern regarding the effects of attention-driven digital platforms on productivity. Digital technologies continuously compete for user attention through notifications, personalized content, algorithmically curated feeds, and engagement-maximizing design features. While these technologies provide significant benefits in terms of communication, information access, and connectivity, they may also impose cognitive and behavioural costs that reduce productivity. Researchers have therefore begun examining how excessive digital engagement affects concentration, task performance, decision-making, and overall efficiency (Wu, 2016).

From an economic perspective, productivity losses associated with excessive digital engagement may be interpreted as unintended consequences of attention-based business models. Digital platforms derive benefits from increased user engagement, whereas users may bear the costs of distraction, reduced concentration, interrupted workflows, and diminished task performance. Such outcomes are particularly relevant within discussions of market failure because the private incentives of platforms may not align with broader social welfare objectives.

2.5.1 Cognitive Costs of Digital Engagement

One of the most significant consequences of excessive digital engagement is the cognitive burden imposed on individuals. Simon (1971) argued that an abundance of information creates a scarcity of attention because human cognitive capacity remains limited. In digital environments characterized by continuous streams of information, notifications, advertisements, and social interactions, individuals must constantly allocate attention across competing demands. This process may reduce the ability to sustain focus on cognitively demanding tasks.

A major cognitive cost associated with digital technology use is task switching. Task switching occurs when individuals repeatedly alternate between different activities, such as responding to messages while working, checking social media during study sessions, or shifting between multiple digital applications. Ophir et al. (2009) found that frequent media multitaskers often experience greater difficulty filtering ir-

relevant information and maintaining attention on primary tasks. Because attention must be repeatedly redirected from one activity to another, task switching increases cognitive effort and reduces overall efficiency.

Another important consequence is attention fragmentation, which refers to the division of attention across multiple competing stimuli. Digital environments expose users to continuous notifications, content updates, messages, and information streams, making sustained concentration increasingly difficult. Mark et al. (2015) reported that frequent interruptions can substantially reduce productivity by disrupting workflow continuity and increasing the time required to regain focus. As a result, fragmented attention may impair information processing, reduce task accuracy, and lower overall performance.

Excessive digital engagement may also contribute to reduced concentration and diminished cognitive control. Carr (2010) argued that continuous interaction with digital technologies encourages rapid attentional shifts and superficial information processing, potentially undermining the ability to engage in deep thinking and sustained reflection. Over time, such patterns may weaken individuals' capacity to maintain prolonged focus on complex tasks requiring sustained cognitive effort.

From a behavioural-economic perspective, these outcomes arise because attention is both scarce and vulnerable to external influences. Digital platforms are specifically designed to attract and retain user attention through persuasive technologies and engagement-enhancing features. Consequently, users may allocate increasing amounts of cognitive resources to digital interactions at the expense of productive activities. This diversion of attention may reduce efficiency, increase mental fatigue, and contribute to lower levels of productivity.

Collectively, these findings suggest that attention-driven digital environments impose significant cognitive costs on users. Through mechanisms such as task switching, attention fragmentation, frequent interruptions, and reduced concentration, excessive digital engagement may diminish individuals' ability to perform tasks effectively and efficiently. These cognitive costs provide an important theoretical explanation for how the Attention Economy may contribute to Productivity Loss, a central outcome examined in the present study.

2.5.2 Workplace Productivity

The influence of digital technologies on workplace productivity has attracted considerable scholarly attention. While digital tools have significantly improved communication, information sharing, collaboration, and operational efficiency, they have also introduced new sources of distraction that may interfere with employee performance. As organizations become increasingly dependent on digital technologies, concerns have emerged regarding the impact of attention-driven digital environments on concentration, task completion, and overall workplace productivity.

One of the most frequently identified sources of productivity loss is digital distraction. Employees are routinely exposed to emails, instant messaging applications, social media platforms, collaborative software, and various online notifications throughout the workday. Although these technologies facilitate communication and information

exchange, they also create frequent interruptions that divert attention away from primary work-related activities. Mark et al. (2015) found that repeated interruptions can significantly reduce productivity by disrupting workflow continuity and increasing the time required to resume complex tasks.

A related concern is notification overload, which occurs when individuals are exposed to excessive numbers of digital alerts, reminders, and prompts. Notifications are intentionally designed to attract immediate attention and encourage user engagement. Duke and Montag (2017) argued that constant exposure to notifications may increase cognitive load and contribute to reduced concentration, stress, and diminished task performance. Since attention is limited, frequent interruptions require individuals to repeatedly reallocate cognitive resources, thereby reducing efficiency and increasing mental effort.

Research further suggests that interruptions impose hidden productivity costs because individuals often require additional time to regain focus after an interruption occurs. Mark et al. (2015) observed that task resumption frequently involves cognitive adjustment and reconstruction of mental context, increasing both completion time and psychological stress. Consequently, even brief interruptions may generate substantial cumulative productivity losses over the course of a workday.

From the perspective of the Attention Economy, these outcomes are particularly significant because many digital platforms derive economic value from maximizing user engagement. Notifications, personalized recommendations, algorithmically curated content, and engagement-enhancing features are designed to attract and retain user attention. While such mechanisms increase platform revenues and user activity, they may simultaneously reduce workplace productivity by encouraging employees to allocate attention toward non-work-related digital interactions (Wu, 2016).

The concept of bounded rationality provides an additional explanation for these outcomes. Simon (1957) argued that individuals possess limited cognitive resources and are therefore unable to process all available information optimally. In digital environments characterized by continuous streams of information and competing demands for attention, employees may struggle to prioritize tasks effectively and resist engagement with distracting digital content. As a result, productivity may decline even when individuals are aware of the potential negative consequences of excessive digital engagement.

From an economic perspective, workplace productivity losses may be interpreted as a negative externality associated with attention-driven business models. Digital platforms benefit from increased engagement and prolonged user attention, whereas employers and employees often bear the costs of reduced concentration, interrupted workflows, lower efficiency, and diminished output. This divergence between private platform incentives and broader economic welfare provides further evidence that the Attention Economy may contribute to market failure.

Overall, the literature suggests that excessive digital engagement can adversely affect workplace productivity through mechanisms such as digital distraction, notification overload, frequent interruptions, and cognitive overload. These findings are particularly relevant to the present study because they provide theoretical support for the proposition that Screen Addiction may contribute to Productivity Loss within attention-

driven digital environments.

2.5.3 Educational Productivity

The effects of digital distractions are particularly evident within educational settings, where sustained attention and cognitive engagement are essential for effective learning. Digital technologies have become integral to contemporary education by facilitating access to information, online learning resources, virtual classrooms, and collaborative learning environments. However, the same technologies that support educational activities may simultaneously create distractions that interfere with academic performance and learning outcomes.

One important concern is reduced academic performance resulting from excessive screen usage and social media engagement. Junco (2012) found that students who frequently engaged with social networking platforms during study sessions often demonstrated lower academic achievement compared with those who experienced fewer digital interruptions. Excessive digital engagement may reduce study efficiency, impair information retention, and decrease the amount of time devoted to academic activities, thereby negatively affecting educational productivity.

Another significant issue is study interruption. Smartphones, social media applications, messaging platforms, and other digital technologies frequently interrupt learning activities through notifications, messages, and incoming communications. Rosen et al. (2013) reported that such interruptions fragment attention, disrupt cognitive processing, and reduce learning effectiveness. Because attention must be repeatedly redirected from academic tasks to digital stimuli, students often experience reduced concentration and lower levels of task completion.

Frequent interruptions may also contribute to procrastination and ineffective time management. Digital platforms provide immediate sources of entertainment, social interaction, and information, making it easier for students to postpone academic responsibilities. As a result, students may devote increasing amounts of time to attention-capturing digital activities at the expense of educational tasks, ultimately reducing academic productivity.

Another important concern is media multitasking, which occurs when students simultaneously engage in educational activities and digital entertainment. Activities such as browsing social media, responding to messages, watching online videos, or surfing the internet while studying divide cognitive resources across multiple tasks. Junco (2012) found that students who frequently multitask during study sessions often experience lower levels of concentration, weaker academic performance, and reduced learning efficiency.

From the perspective of Attention Scarcity Theory, educational productivity depends heavily on the effective allocation of limited cognitive resources. Simon (1971) argued that an abundance of information creates a scarcity of attention because individuals possess finite cognitive capacity. In digitally saturated learning environments, students are exposed to numerous competing demands for attention, making sustained focus increasingly difficult. Consequently, excessive engagement with digital platforms may undermine the concentration required for effective learning and academic

achievement.

The Attention Economy further intensifies these challenges because many digital platforms are specifically designed to capture and retain user attention through personalized recommendations, notifications, algorithmically curated content, and social feedback mechanisms. While such features increase engagement and platform profitability, they may simultaneously divert students' attention away from educational objectives and contribute to reduced academic productivity (Wu, 2016).

Overall, the literature suggests that excessive digital engagement may adversely affect educational productivity through study interruptions, procrastination, media multitasking, fragmented attention, and reduced concentration. These findings are particularly relevant to the present study because they provide further evidence regarding the potential relationship between Screen Addiction and Productivity Loss within attention-driven digital environments.

2.5.4 Productivity Loss in the Attention Economy

The literature reviewed in the preceding sections suggests that productivity loss is one of the most significant consequences of attention-driven digital environments. Although digital technologies have improved communication, information access, and operational efficiency, they have also created new challenges associated with attention allocation and cognitive resource management. As individuals increasingly interact with digital platforms designed to maximize engagement, concerns have emerged regarding their ability to maintain concentration, complete tasks efficiently, and sustain productive behaviour.

Several studies indicate that excessive digital engagement may reduce productivity through multiple behavioural and cognitive mechanisms. Simon (1971) argued that an abundance of information creates a scarcity of attention, implying that individuals possess limited cognitive resources for processing information and performing tasks. Building upon this perspective, Ophir et al. (2009) found that frequent media multitasking impairs cognitive control and increases susceptibility to distraction. Similarly, Mark et al. (2015) reported that repeated interruptions disrupt workflow continuity and increase the time required to regain concentration after task switching. These findings suggest that attention fragmentation, digital distraction, and notification overload may collectively reduce individual productivity.

The literature further indicates that behavioural dependency on digital platforms may intensify productivity-related challenges. Griffiths (2005) explained that behavioural addictions are characterized by compulsive engagement in rewarding activities despite adverse consequences. In digital environments, engagement-enhancing features such as personalized recommendations, notifications, social feedback mechanisms, and variable reward structures encourage prolonged platform use. Alter (2017) observed that these mechanisms can contribute to habitual and compulsive patterns of digital engagement, potentially diverting attention away from productive activities.

From the perspective of the Attention Economy, productivity loss can be interpreted as an unintended consequence of attention-based business models. Wu (2016) argued that digital platforms compete intensely for user attention because engagement

directly influences advertising revenue and platform profitability. Consequently, platform design often prioritizes user retention and prolonged interaction. While such strategies generate economic benefits for platform providers, they may simultaneously reduce users' efficiency by encouraging frequent interruptions, excessive screen engagement, and compulsive usage behaviour.

This divergence between private benefits and social costs is consistent with the concept of negative externalities. Digital platforms capture economic value through increased engagement, whereas users, employers, educational institutions, and society bear the costs associated with reduced concentration, diminished efficiency, and lower productivity. Such outcomes suggest the possibility of market failure, whereby the social costs of attention-capturing digital environments are not fully reflected in market transactions.

In the context of the present study, Productivity Loss (PL) represents a key outcome variable through which the broader economic implications of the Attention Economy can be examined. The existing literature suggests that Screen Use Intensity and, more importantly, Screen Addiction may contribute to productivity loss by increasing interruptions, reducing concentration, and encouraging compulsive engagement with digital platforms. Understanding these relationships is therefore essential for evaluating whether attention-driven digital markets generate welfare losses and contribute to market failure.

2.6 Market Failure in the Attention Economy

The concept of market failure occupies a central position in economic theory and refers to situations in which market mechanisms fail to allocate resources efficiently, resulting in outcomes that do not maximize social welfare. Stiglitz and Rosengard (2015) explained that market failure typically arises from factors such as externalities, information asymmetry, and market power, all of which prevent markets from achieving socially optimal outcomes. Although these concepts were originally developed to explain failures in traditional markets, they have become increasingly relevant in the analysis of digital platforms and attention-driven business models.

The emergence of the Attention Economy has transformed human attention into a valuable economic resource. Digital platforms compete intensely to capture, retain, and monetize user attention through personalized content, recommendation algorithms, notifications, and other engagement-enhancing mechanisms. Wu (2016) argued that contemporary digital firms operate as "attention merchants" whose profitability depends on maximizing user engagement and screen time. Similarly, Zuboff (2019) observed that digital platforms increasingly rely on behavioural data and predictive systems to influence user behaviour and sustain engagement.

While these business models generate substantial economic value, they may also produce outcomes that are not socially efficient. The benefits associated with increased user engagement largely accrue to platform providers through advertising revenue, data monetization, and market expansion. However, many of the costs associated with excessive digital engagement are borne by users and society. These costs may include screen addiction, reduced productivity, psychological distress, diminished well-being,

and the erosion of individual autonomy. Since such costs are generally not reflected in market prices, digital platforms may have limited incentives to internalize them.

The Attention Economy therefore raises important concerns regarding the alignment between private incentives and social welfare. Platforms are rewarded for maximizing engagement regardless of whether prolonged engagement contributes positively or negatively to user well-being. As a result, market outcomes may encourage levels of digital consumption that exceed socially desirable levels. This divergence between private benefits and social costs is a defining characteristic of market failure.

Two forms of market failure are particularly relevant to the present study. The first is the existence of negative externalities arising from excessive digital engagement. Productivity loss, mental health deterioration, and addictive patterns of behaviour may impose costs on individuals, families, educational institutions, employers, and society more broadly. The second is information asymmetry, whereby digital platforms possess substantially greater knowledge regarding user behaviour, algorithmic systems, and engagement strategies than the users themselves. Akerlof (1970) demonstrated that such informational imbalances can distort decision-making and produce inefficient market outcomes.

From a behavioural-economic perspective, these issues are further amplified by bounded rationality and persuasive platform design. Users often make decisions under conditions of limited information, cognitive constraints, and behavioural influences. Consequently, they may underestimate the long-term consequences of excessive digital engagement or fail to recognize the mechanisms through which their attention is being captured and monetized. Such conditions increase the likelihood that digital markets will generate welfare losses that are not adequately addressed through market forces alone.

Accordingly, the Attention Economy provides a useful context for examining contemporary forms of market failure. By linking Digital Access, Asymmetric Information, Screen Use Intensity, Screen Addiction, Productivity Loss, and Mental Health Impact, the present study seeks to investigate whether attention-driven digital markets generate outcomes that are consistent with the economic theory of market failure.

2.6.1 Negative Externalities

Negative externalities arise when the actions of producers or consumers impose costs on third parties that are not reflected in market prices. Pigou (1920) argued that when private decision-makers do not bear the full social costs of their actions, market outcomes deviate from socially optimal levels, resulting in welfare losses. In such circumstances, market mechanisms encourage levels of production or consumption that exceed those which would prevail if all costs were fully internalized.

The concept of negative externalities is particularly relevant to the Attention Economy. Digital platforms generate revenue primarily by attracting, retaining, and monetizing user attention. Through advertising-based business models, personalized content, recommendation algorithms, and engagement-enhancing design features, platforms have strong incentives to maximize user interaction and screen time. Wu (2016) observed that the economic success of digital platforms depends largely on their ability

to capture and retain attention, transforming user engagement into a valuable commercial asset.

While increased engagement generates substantial benefits for platform providers, many of the associated costs are borne by users and society rather than by the platforms themselves. As a result, the private benefits derived from attention extraction may exceed the social benefits generated by such activities. This divergence between private incentives and social welfare is a defining characteristic of negative externalities and provides an important basis for understanding market failure within digital ecosystems.

One major category of external costs relates to mental health and psychological well-being. Twenge and Campbell (2018) found that higher levels of screen exposure were associated with lower psychological well-being and increased risks of emotional distress among young users. Similarly, Primack et al. (2017) reported that intensive social media use was associated with greater levels of perceived social isolation. These findings suggest that prolonged engagement with digital platforms may generate psychological costs that are not reflected in the market value created by platform activity.

A second category of external costs concerns productivity and economic efficiency. Mark et al. (2015) demonstrated that frequent digital interruptions disrupt workflow continuity and reduce task performance. Likewise, Rosen et al. (2013) observed that media-induced task switching impairs concentration and learning effectiveness among students. Because reduced productivity affects educational institutions, employers, and economic output more broadly, the costs associated with excessive digital engagement extend beyond individual users.

Negative externalities may also emerge in the form of broader social and behavioural consequences. Carr (2010) argued that continuous exposure to digital information may weaken sustained concentration and encourage superficial information processing. Furthermore, excessive dependence on digital technologies may reduce the quality of interpersonal interactions, increase social isolation, and contribute to declining attention spans. Although these effects are difficult to quantify directly, they represent social costs that are largely absent from conventional market transactions.

From an economic perspective, these outcomes indicate that attention-driven digital markets may generate levels of engagement that exceed socially desirable levels. Since platform providers capture the benefits associated with prolonged engagement while users and society bear many of the resulting costs, market outcomes may become inefficient. Consequently, negative externalities provide an important theoretical explanation for how the Attention Economy may contribute to market failure.

In the context of the present study, Productivity Loss (PL) and Mental Health Impact (MHI) are conceptualized as important manifestations of the negative externalities generated by attention-driven digital markets. The examination of these outcomes therefore provides an empirical basis for assessing whether the Attention Economy contributes to welfare losses and inefficient market outcomes.

2.6.2 Information Asymmetry

Information asymmetry arises when one party to an economic relationship possesses substantially more information than another. Akerlof (1970) demonstrated that such

informational imbalances can distort decision-making, reduce market efficiency, and generate welfare losses. In situations where consumers lack access to relevant information, they may be unable to evaluate alternatives accurately or make decisions that maximize their welfare. Consequently, information asymmetry has long been recognized as a significant source of market failure in economic theory.

The concept has become increasingly relevant in the digital economy, particularly within the Attention Economy. Digital platforms possess extensive information regarding user behaviour, engagement patterns, content preferences, and algorithmic performance. Through large-scale data collection and advanced analytics, platforms continuously monitor user activities and utilize these insights to optimize engagement strategies. In contrast, users generally possess limited knowledge regarding how algorithms operate, how content is selected, and how their personal data are utilized. This imbalance creates a substantial asymmetry of information between platforms and users.

One important manifestation of information asymmetry involves algorithmic opacity. Pasquale (2015) argued that many digital systems operate as "black boxes," where the processes governing content selection, recommendation, and ranking remain largely invisible to users. Recommendation algorithms determine which content is displayed, prioritized, or suppressed; however, users often have little understanding of the criteria underlying these decisions. Consequently, individuals may unknowingly interact with information environments that have been strategically designed to maximize engagement and attention retention.

A second manifestation relates to behavioural data collection and monetization. Zuboff (2019) observed that digital platforms routinely collect extensive behavioural data generated through online interactions, searches, clicks, purchases, and social activities. These data are subsequently analysed to predict user behaviour, personalize content, and improve advertising effectiveness. Although users formally consent to such practices through privacy policies and terms of service agreements, these documents are frequently complex, lengthy, and difficult to understand. As a result, many users remain unaware of the extent to which their behaviour is monitored, analysed, and commercialized.

Information asymmetry may also influence consumer autonomy and decision-making. When users possess incomplete information regarding platform operations, they may underestimate the extent to which engagement-enhancing mechanisms influence their behaviour. Akerlof (1970) argued that decisions made under conditions of incomplete information are often less efficient than those made under conditions of full information. Within digital markets, such informational imbalances may reduce users' ability to make informed choices regarding screen usage, platform engagement, and data-sharing practices.

From a behavioural-economic perspective, the effects of information asymmetry are amplified by bounded rationality. Simon (1957) argued that individuals possess limited cognitive capacity and therefore cannot process all available information effectively. Even when information regarding data practices and algorithmic systems is technically available, users may lack the time, expertise, or motivation required to fully understand it. Consequently, informational disadvantages may persist despite formal

disclosure requirements.

The Attention Economy further intensifies these challenges because platform profitability depends heavily on user engagement. Digital firms continuously refine algorithms, recommendation systems, notifications, and personalized content feeds to increase attention retention and screen time. Since platforms possess substantially more information regarding the effectiveness of these mechanisms than users, they are able to influence behaviour in ways that may not be fully transparent. Wu (2016) argued that the economic success of attention-based platforms depends largely on their ability to capture and retain user attention, while Zuboff (2019) suggested that behavioural prediction and modification have become central components of contemporary digital business models.

From the perspective of market failure, information asymmetry may lead to inefficient outcomes because users are unable to make fully informed decisions regarding their digital behaviour. The resulting imbalance between platform knowledge and user awareness may contribute to excessive screen engagement, increased susceptibility to persuasive design mechanisms, and greater risks of behavioural dependency. Consequently, information asymmetry represents a critical mechanism through which the Attention Economy may generate welfare losses.

In the context of the present study, Asymmetric Information (AS) is conceptualized as a key determinant of digital behaviour. It is proposed that higher levels of information asymmetry increase Screen Use Intensity (SUI) and Screen Addiction (SA) by reducing users' awareness of the mechanisms through which their attention is captured and monetized. Furthermore, information asymmetry may strengthen the relationship between Digital Access (DA) and digital engagement outcomes, thereby serving as an important moderating factor within the conceptual framework of the study.

Table 2.1: Summary of Empirical Studies Relevant to the Present Research

Author(s)	Year	Context / Sample	Variables Examined	Method	Major Findings	Research Gap
Davey and Davey	2014	Indian adolescents	Smartphone addiction and behavioural outcomes	Mixed-method	High prevalence of smartphone addiction and behavioural dependence.	No examination of causal pathways linking digital access, addiction, productivity, and mental health.
Nikhita et al.	2015	Indian secondary school students	Mobile phone dependence	Cross-sectional survey	Significant prevalence of mobile phone dependence.	Focused only on prevalence; no causal modelling.
Gupta and Bashir	2018	Indian university students	Social networking usage	Scale development	Social media usage influences behavioural engagement.	Did not examine productivity, mental health, or market failure.
Soni et al.	2017	Medical students	Smartphone addiction and sleep quality	Survey analysis	Smartphone addiction associated with poor sleep quality.	Limited focus on broader economic and behavioural implications.
Singh et al.	2020	Indian youth during COVID-19	Digital engagement and mental health	Literature review	Digital engagement linked with psychological distress.	No empirical structural model testing.
Keles et al.	2020	Adolescents	Social media use, anxiety and depression	Systematic review	Association between social media use and mental health problems.	Predominantly correlational evidence.
Twenge and Campbell	2018	Adolescents	Screen time and psychological well-being	Large-scale survey	Higher screen time associated with lower well-being.	Did not examine addiction and information asymmetry mechanisms.
Primack et al.	2017	Young adults	Social media use and psychological distress	National survey	Greater social media use associated with psychological distress.	Limited attention to platform incentives and attention capture.
Wu	2016	Attention economy	Attention capture and monetisation	Theoretical analysis	Platforms monetise user attention through engagement strategies.	No empirical testing of behavioural outcomes.
Zuboff	2019	Digital platforms	Surveillance capitalism and behavioural data	Theoretical analysis	Behavioural data used to predict and influence engagement.	Limited empirical validation of behavioural pathways.

Table 2.1 shows that existing studies largely examine digital engagement, addiction, and mental health outcomes separately. Most empirical studies rely on descriptive, cross-sectional, or correlational approaches and do not examine the direct, indirect, and moderating relationships among Digital Access, Asymmetric Information, Screen Use Intensity, Screen Addiction, Productivity Loss, and Mental Health Impact within a unified behavioural-economic framework. This gap provides the basis for the present study.

2.7 Conceptual Framework of the Study

The conceptual framework provides a theoretical representation of the relationships among the key constructs examined in the present study. It is developed based on insights derived from Attention Economy Theory, Attention Scarcity Theory, Behavioural Economics, Information Asymmetry Theory, and Market Failure Theory. Collectively, these theoretical perspectives suggest that digital platforms compete intensively for user attention and employ various technological and behavioural mechanisms to increase engagement, thereby influencing individual behaviour and welfare outcomes.

The framework conceptualizes Degree of Digital Access (DA) as the primary antecedent variable. Digital access reflects the extent to which individuals can interact with digital technologies through smartphones, internet connectivity, social media platforms, and other online services. Greater access to digital technologies increases opportunities for online engagement and exposure to attention-capturing mechanisms embedded within digital platforms. Consequently, higher levels of digital access are expected to increase both Screen Use Intensity (SUI) and Screen Addiction (SA).

Screen Use Intensity (SUI) represents the extent and frequency of engagement with digital devices and online platforms. Consistent with Attention Economy Theory, greater digital access is expected to increase the amount of time and attention allocated to digital environments. However, prolonged and repeated engagement may, over time, develop into more persistent and compulsive patterns of behaviour, represented by Screen Addiction (SA).

Screen Addiction (SA) is conceptualized as a behavioural outcome arising from excessive and uncontrolled digital engagement. Drawing upon Behavioural Addiction Theory and Reinforcement Theory, the framework proposes that addictive patterns of digital behaviour emerge when users repeatedly interact with engagement-enhancing features such as personalized recommendations, social feedback mechanisms, notifications, and variable reward structures. Such behaviours may subsequently affect broader aspects of individual well-being and performance.

The framework further proposes that Screen Use Intensity and Screen Addiction influence two important outcome variables: Productivity Loss (PL) and Mental Health Impact (MHI). Excessive engagement with digital platforms may reduce concentration, increase interruptions, fragment attention, and impair task performance, thereby contributing to productivity-related losses. Similarly, prolonged digital engagement and addictive usage patterns may adversely affect psychological well-being through increased stress, anxiety, emotional exhaustion, sleep disruption, and other mental health concerns.

An important feature of the conceptual framework is the inclusion of Asymmetric Information (AS). Information Asymmetry Theory suggests that digital platforms possess substantially greater knowledge regarding user behaviour, algorithmic systems, engagement optimization techniques, and behavioural targeting mechanisms than users themselves. This informational imbalance may influence how individuals interact with digital technologies and respond to attention-capturing strategies.

Accordingly, Asymmetric Information is incorporated into the framework in two ways. First, it is conceptualized as a direct determinant of Screen Use Intensity and Screen Addiction because users who possess limited understanding of platform operations may be more susceptible to engagement-enhancing mechanisms. Second, Asymmetric Information is expected to strengthen the relationship between Digital Access and digital engagement outcomes. Individuals with greater digital access may be particularly vulnerable to excessive usage and addictive behaviours when informational imbalances regarding platform practices remain high.

From a broader economic perspective, the framework integrates concepts of market failure by proposing that Productivity Loss and Mental Health Impact represent potential negative externalities generated by attention-driven digital markets. While digital platforms benefit from increased user engagement, many of the associated social and psychological costs are borne by users and society. Consequently, the framework provides a behavioural-economic explanation of how the Attention Economy may contribute to welfare losses through excessive digital engagement and informational imbalances.

The conceptual framework therefore provides a comprehensive structure for examining the direct, indirect, and moderating relationships among Digital Access, Screen Use Intensity, Screen Addiction, Productivity Loss, Mental Health Impact, and Asymmetric Information. These relationships form the basis for the hypotheses developed in the subsequent section and guide the empirical analysis undertaken in this study.

2.8 Proposed Research Model

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Based on the theoretical foundations and empirical literature reviewed in this chapter, the proposed research model was developed to examine the relationships among Digital Access, Asymmetric Information, Screen Use Intensity, Screen Addiction, Impact on Productivity, and Mental Hygiene. The model also incorporates the moderating effect of Asymmetric Information on the relationship between Digital Access and digital engagement outcomes.

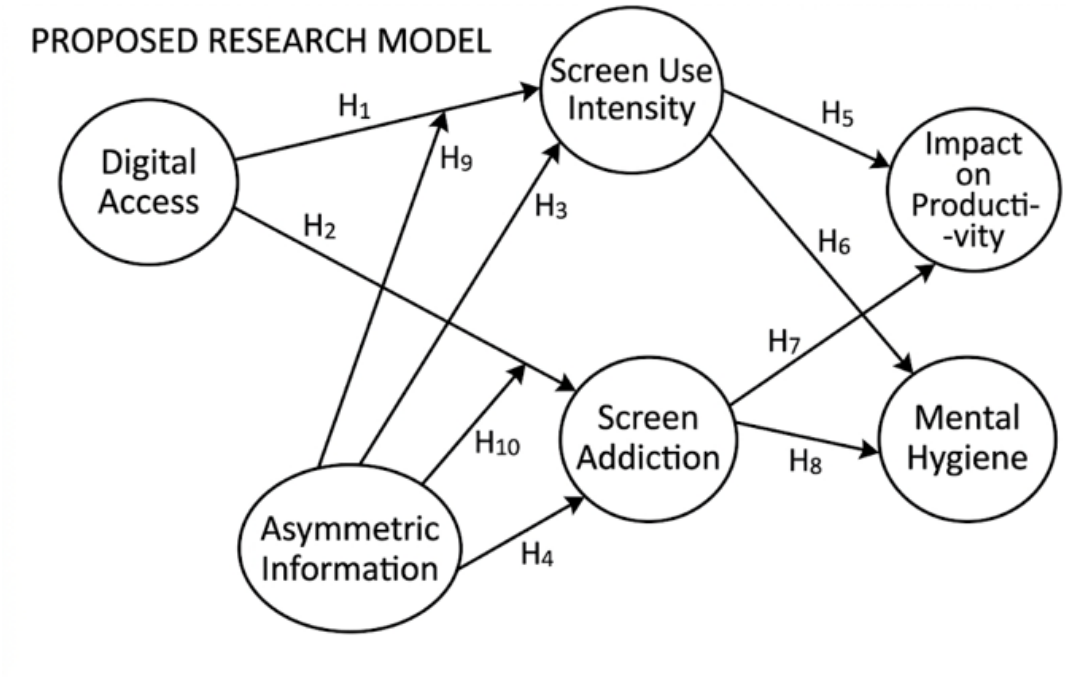


Figure 2.1: Proposed Research Model

Figure 2.1 presents the hypothesized relationships among the study variables. The model proposes that Digital Access and Asymmetric Information influence Screen Use Intensity and Screen Addiction, which subsequently affect Impact on Productivity and Mental Hygiene. In addition, Asymmetric Information is proposed to moderate the relationship between Digital Access and both Screen Use Intensity and Screen Addiction.

2.9 Hypothesis Development

The conceptual framework developed in the present study is grounded in the theoretical foundations of the Attention Economy, Behavioural Economics, Information Asymmetry Theory, and Market Failure Theory. The literature reviewed in the preceding sections suggests that digital platforms influence user behaviour through attention-capturing mechanisms, personalized content delivery, algorithmic recommendations, and engagement optimization strategies. These mechanisms are expected to affect users' screen usage behaviour and may subsequently generate broader productivity and mental health consequences.

Drawing upon the theoretical arguments and empirical evidence discussed in this chapter, the present study proposes a set of hypotheses to examine the relationships among Digital Access, Asymmetric Information, Screen Use Intensity, Screen Addiction, Impact on Productivity, and Mental Hygiene. In addition, the study investigates whether Asymmetric Information moderates the influence of Digital Access on digital engagement outcomes. The proposed hypotheses are presented below.

H1: Digital Access has a significant positive effect on Screen Use Intensity.

H2: Digital Access has a significant positive effect on Screen Addiction.

H3: Asymmetric Information has a significant positive effect on Screen Use Intensity.

H4: Asymmetric Information has a significant positive effect on Screen Addiction.

H5: Screen Use Intensity has a significant effect on Impact on Productivity.

H6: Screen Use Intensity has a significant effect on Mental Hygiene.

H7: Screen Addiction has a significant effect on Impact on Productivity.

H8: Screen Addiction has a significant effect on Mental Hygiene.

H9: Asymmetric Information moderates the relationship between Digital Access and Screen Use Intensity.

H10: Asymmetric Information moderates the relationship between Digital Access and Screen Addiction.

The above hypotheses collectively examine the direct effects of Digital Access and Asymmetric Information on digital engagement behaviours, the effects of Screen Use Intensity and Screen Addiction on productivity and mental health outcomes, and the moderating role of Asymmetric Information within the Attention Economy framework. The empirical testing of these hypotheses is undertaken in the subsequent chapters using Partial Least Squares Structural Equation Modelling (PLS-SEM).

2.10 Conclusion

This chapter reviewed the theoretical and empirical literature relating to the Attention Economy and its behavioural and economic implications. The review examined the evolution of attention as a scarce economic resource and discussed the theoretical contributions of Simon's Theory of Attention Scarcity, Goldhaber's Attention Economy Theory, Wu's Attention Merchants Framework, and Zuboff's Surveillance Capitalism. Collectively, these theories provide a comprehensive explanation of how digital platforms compete for, capture, and monetize user attention within contemporary digital markets.

The chapter further explored the behavioural mechanisms underlying digital engagement, including bounded rationality, persuasive technology, behavioural manipulation, information asymmetry, and algorithmic attention capture. The literature suggests that digital platforms increasingly employ personalized content, recommendation systems, notifications, and other engagement-enhancing mechanisms to influence user behaviour and maximize attention retention. These practices have important implications for screen usage behaviour, behavioural dependency, productivity, and psychological well-being.

The empirical literature reviewed in this chapter indicates that excessive digital engagement has been associated with a range of adverse outcomes, including screen

addiction, reduced productivity, anxiety, depression, loneliness, sleep disruption, and emotional exhaustion. However, the existing evidence remains fragmented, with most studies focusing on isolated relationships rather than examining the broader behavioural and economic mechanisms through which digital platforms influence user outcomes. Furthermore, much of the existing research relies on correlational approaches and provides limited insight into causal pathways.

The review also highlighted the relevance of Market Failure Theory in understanding the Attention Economy. Negative externalities arising from excessive digital engagement and information asymmetries between platforms and users suggest that digital markets may generate outcomes that deviate from socially optimal levels. The literature indicates that while digital platforms derive significant economic benefits from increased user engagement, many of the associated social and psychological costs are borne by individuals and society.

The synthesis of theoretical and empirical studies revealed several important research gaps. Existing studies rarely integrate Digital Access, Asymmetric Information, Screen Use Intensity, Screen Addiction, Impact on Productivity, and Mental Hygiene within a unified analytical framework. In addition, limited research has examined the moderating role of information asymmetry or investigated the Attention Economy from a behavioural-economic and market-failure perspective using advanced causal modelling techniques.

To address these gaps, the chapter developed a comprehensive conceptual framework and proposed ten research hypotheses linking Digital Access, Asymmetric Information, Screen Use Intensity, Screen Addiction, Impact on Productivity, and Mental Hygiene. These relationships provide the theoretical foundation for the empirical investigation undertaken in this study.

Having established the theoretical foundations, research gaps, conceptual framework, and hypotheses, the next chapter presents the research methodology adopted for the study. It discusses the research design, sampling procedure, data collection methods, measurement instruments, and analytical techniques employed to empirically test the proposed model using Partial Least Squares Structural Equation Modelling (PLS-SEM).

Chapter 3

RESEARCH METHODOLOGY

3.1 Introduction

This chapter describes the methodological framework adopted to examine the relationships among Digital Access (DA), Screen Use Intensity (SUI), Screen Addiction (SA), Impact on Productivity (IP), Mental Hygiene (MH), and Asymmetric Information (AS) within the context of the Attention Economy. It outlines the research philosophy, research approach, research design, sampling strategy, data collection procedures, measurement of variables, and analytical techniques employed to achieve the objectives of the study.

Given the behavioural and causal nature of the research problem, the study adopts a quantitative research methodology. Primary data were collected through a structured questionnaire administered to digital platform users. The quantitative approach enables the systematic measurement of latent constructs and facilitates the empirical testing of the hypothesized relationships proposed in the conceptual framework.

Considering the multidimensional nature of the study and the presence of multiple endogenous and exogenous constructs, Partial Least Squares Structural Equation Modelling (PLS-SEM) has been employed as the principal analytical technique. Hair et al. (2022) stated that PLS-SEM is particularly appropriate for predictive research, theory development, and the analysis of complex models involving multiple relationships, mediating mechanisms, and moderating effects. The technique simultaneously evaluates the measurement properties of constructs and the structural relationships among them.

The methodology adopted in this study is designed to provide robust empirical evidence regarding the behavioural pathways through which digital access and information asymmetry influence digital engagement outcomes and their subsequent effects on productivity and mental well-being. The chapter therefore establishes the methodological foundation for testing the proposed research model and evaluating the study hypotheses.

3.2 Research Philosophy

Research philosophy refers to the set of assumptions and beliefs that guide the collection, analysis, and interpretation of data in a research study. According to Saunders et al. (2019), the choice of research philosophy influences methodological decisions and determines how knowledge is generated and evaluated.

The present study adopts the positivist research philosophy. Positivism assumes that reality exists independently of the researcher and can be objectively observed, measured, and explained through empirical investigation. Bryman (2016) stated that positivist research emphasizes the application of scientific methods to examine social phenomena, test theoretical propositions, and identify causal relationships through systematic observation and statistical analysis.

The adoption of positivism is appropriate for the present study for several reasons. First, the study seeks to empirically test a set of hypotheses derived from established theoretical perspectives, including Attention Scarcity Theory, Attention Economy Theory, Information Asymmetry Theory, and Market Failure Theory. Positivism supports the development and testing of hypotheses using observable and measurable data.

Second, the key constructs examined in the study, namely Digital Access, Screen Use Intensity, Screen Addiction, Impact on Productivity, Mental Hygiene, and Asymmetric Information, are measured using structured questionnaire items. The use of standardized measurement instruments enables the quantification of abstract concepts and facilitates objective statistical analysis.

Third, the study employs Partial Least Squares Structural Equation Modelling (PLS-SEM) to examine the proposed relationships among the constructs. Hair et al. (2022) noted that PLS-SEM is particularly suitable for predictive and explanatory research involving multiple latent variables, complex structural relationships, and moderation effects. The technique aligns with the positivist objective of testing theoretical relationships through empirical evidence.

Finally, the study aims to generate objective and generalizable findings regarding the behavioural and economic consequences of digital engagement. Consistent with the positivist paradigm, the emphasis is placed on empirical measurement, statistical validation, and theory testing rather than subjective interpretation.

Therefore, the positivist philosophy provides an appropriate foundation for examining the causal relationships proposed in the conceptual model and for evaluating the behavioural-economic implications of the Attention Economy.

3.3 Research Approach

The present study adopts a deductive research approach. Deductive research involves deriving hypotheses from established theories and subsequently testing them through empirical investigation. According to Saunders et al. (2019), the deductive approach proceeds from theory to observation and is particularly suitable for studies that seek to validate theoretical propositions using quantitative data.

The adoption of a deductive approach is appropriate because the study is grounded in established theoretical perspectives, including Attention Scarcity Theory, Attention

Economy Theory, Information Asymmetry Theory, and Market Failure Theory. These theories provide the conceptual basis for explaining how digital access and information asymmetry influence digital engagement behaviours and their subsequent effects on productivity and mental well-being.

The research process followed a systematic sequence. Initially, an extensive review of theoretical and empirical literature was undertaken to identify the key constructs and relationships relevant to the study. Based on this review, a conceptual framework was developed and a set of hypotheses was formulated. Subsequently, primary data were collected through a structured questionnaire administered to digitally active respondents. The collected data were then analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) to evaluate the proposed relationships and test the study hypotheses.

The deductive approach enables the empirical examination of theoretically derived relationships and facilitates the assessment of the explanatory power of the proposed model. By testing hypotheses grounded in established theories, the study contributes to a better understanding of the behavioural and economic implications of the Attention Economy.

3.4 Research Design

Research design refers to the overall plan and structure adopted for collecting, measuring, and analysing data in order to address the research objectives and answer the research questions (Bryman, 2016). The present study employs a cross-sectional quantitative research design.

A quantitative research design is appropriate because the study seeks to examine relationships among multiple measurable constructs and empirically test a set of hypotheses derived from established theories. Quantitative methods facilitate the objective measurement of behavioural phenomena and enable the application of statistical techniques to analyse relationships among variables.

The study adopts a cross-sectional survey design, whereby data were collected from respondents at a single point in time. According to Saunders et al. (2019), cross-sectional designs are widely used in social science and behavioural research because they enable the collection of standardized data from a large number of respondents within a relatively short period.

The survey approach was considered suitable because it allows the systematic collection of information relating to Digital Access, Screen Use Intensity, Screen Addiction, Impact on Productivity, Mental Hygiene, and Asymmetric Information. The use of standardized measurement scales ensures consistency in data collection and facilitates subsequent statistical analysis.

The study further employs Partial Least Squares Structural Equation Modelling (PLS-SEM) to examine the proposed structural relationships among the latent constructs. Hair et al. (2022) noted that cross-sectional survey data are commonly used in PLS-SEM studies for testing theoretically specified relationships and evaluating complex behavioural models. Accordingly, the adopted research design is appropriate for achieving the objectives of the present study and empirically testing the proposed con-

ceptual framework.

3.5 Population of the Study

The population of a study refers to the complete set of individuals possessing the characteristics relevant to the research objectives (Saunders et al., 2019). The target population for the present study comprises digitally active individuals who regularly use internet-enabled devices and engage with digital platforms such as social media applications, online communication tools, streaming services, educational platforms, and other internet-based services.

To ensure adequate representation of different patterns of digital engagement, the study focuses on three major categories of respondents:

1. School Students
2. College and University Students
3. Working Professionals

These groups were selected because they represent significant segments of digital users and differ in their usage patterns, purposes of engagement, and exposure to digital technologies. School and university students frequently utilize digital platforms for learning, communication, entertainment, and social interaction, whereas working professionals rely on digital technologies for workplace communication, information access, collaboration, and task management.

The inclusion of these respondent categories enables the study to capture variations in Digital Access, Screen Use Intensity, Screen Addiction, Impact on Productivity, Mental Hygiene, and Asymmetric Information across different demographic groups. Such diversity enhances the ability of the study to examine behavioural patterns associated with digital engagement and improves the generalizability of the findings.

Accordingly, the selected population provides an appropriate basis for empirically testing the proposed conceptual framework and examining the relationships among the study variables.

3.6 Sampling Technique and Sample Size

3.6.1 Sampling Technique

Sampling refers to the process of selecting a subset of individuals from a target population to obtain information about the population as a whole (Saunders et al., 2019). Since it was not feasible to collect data from all digitally active individuals, an appropriate sampling strategy was adopted to ensure adequate representation of different user groups.

The present study employed a stratified multistage sampling technique. In the first stage, the target population was divided into three strata based on primary activity:

School Students, College and University Students, and Working Professionals. Stratification was adopted to ensure that each category of digital users was adequately represented in the sample and to capture variations in digital engagement behaviour across different demographic groups.

In the second stage, respondents were selected from educational institutions, professional networks, and online communities. Data were collected through an online questionnaire distributed using digital platforms and communication networks. This approach facilitated access to respondents who regularly use digital technologies and online platforms.

The use of stratified sampling enhanced the representativeness of the sample by ensuring the inclusion of respondents with diverse digital experiences and usage patterns. Such representation was important for examining variations in Digital Access, Screen Use Intensity, Screen Addiction, Impact on Productivity, Mental Hygiene, and Asymmetric Information across different user groups.

Accordingly, the adopted sampling technique was considered appropriate for achieving the objectives of the study and for testing the proposed conceptual framework.

3.6.2 Sample Size

Sample size refers to the number of respondents selected from the target population for the purpose of data collection and analysis. An appropriate sample size is essential for ensuring the reliability of statistical estimates and the robustness of empirical findings (Hair et al., 2022).

The present study obtained responses from a total of 174 respondents comprising School Students, College and University Students, and Working Professionals. The sample was considered adequate for the application of Partial Least Squares Structural Equation Modelling (PLS-SEM), which is widely recognized for its suitability in studies involving complex models, multiple latent constructs, and relatively moderate sample sizes.

According to Hair et al. (2022), PLS-SEM does not require large sample sizes compared to covariance-based structural equation modelling and is particularly appropriate for exploratory and predictive research. The adequacy of the sample was further supported by the complexity of the proposed model, which includes multiple exogenous and endogenous constructs as well as moderating relationships.

The final sample of 174 respondents provided sufficient observations for evaluating the measurement model and testing the structural relationships proposed in the conceptual framework. Accordingly, the sample size was considered appropriate for achieving the objectives of the study and ensuring the validity of the empirical analysis.

3.7 Research Instrument

Primary data for the present study were collected using a structured questionnaire designed to measure the constructs included in the proposed conceptual framework. The questionnaire was developed following an extensive review of the literature on the Attention Economy, digital engagement, information asymmetry, behavioural addic-

tion, productivity, and mental health. Wherever appropriate, measurement items were adapted from established scales and modified to suit the objectives of the study.

The questionnaire comprised seven sections. The first section collected demographic information, while the remaining sections measured the latent constructs included in the research model.

Table 3.1: Structure of the Questionnaire

Section	Construct
Section 1	Demographic Information
Section 2	Digital Access (DA)
Section 3	Screen Use Intensity (SUI)
Section 4	Asymmetric Information (AS)
Section 5	Screen Addiction (SA)
Section 6	Mental Hygiene (MH)
Section 7	Impact on Productivity (IP)

The initial questionnaire consisted of 57 measurement items distributed across the six latent constructs. Responses were recorded using a five-point Likert scale, with response categories ranging from 1 = Strongly Disagree to 5 = Strongly Agree or 1 = Never to 5 = Always, depending on the nature of the item.

Prior to structural model estimation, the measurement instrument was subjected to Exploratory Factor Analysis (EFA) to assess dimensionality and establish preliminary construct validity. Items exhibiting low factor loadings or substantial cross-loadings were removed in accordance with accepted statistical criteria. This process improved construct clarity and strengthened discriminant validity while maintaining theoretical consistency.

The refined measurement instrument obtained after EFA was subsequently used for measurement model assessment and structural model evaluation through Partial Least Squares Structural Equation Modelling (PLS-SEM). The use of a structured questionnaire ensured standardized data collection and facilitated the application of multivariate statistical techniques.

The questionnaire was administered electronically through online survey platforms, enabling efficient data collection from digitally active respondents across different regions of India.

3.8 Measurement of Variables

The present study examines six latent constructs, namely Digital Access (DA), Screen Use Intensity (SUI), Screen Addiction (SA), Impact on Productivity (IP), Mental Hygiene (MH), and Asymmetric Information (AS). All constructs were operationalized using multiple-item measures adapted from established theoretical and empirical literature. Responses were recorded using a five-point Likert scale ranging from 1 (Strongly Disagree/Never) to 5 (Strongly Agree/Always).

Table 3.2: Measurement of Variables and Sources

Construct	Code	Role in Model	No. of Items	Source Basis
Digital Access	DA	Independent Variable	5	Van Dijk (2006); Hargittai (2002)
Screen Use Intensity	SUI	Endogenous Construct	9	Ellison et al. (2007); Junco (2012)
Screen Addiction	SA	Endogenous Construct	9	Young (1998); Kwon et al. (2013)
Impact on Productivity	IP	Dependent Variable	9	Mark et al. (2015); Duke and Montag (2017)
Mental Hygiene	MH	Dependent Variable	15	Ryff (1989); Diener et al. (2010)
Asymmetric Information	AS	Moderating Variable	9	Akerlof (1970); Acquisti et al. (2015); Zuboff (2019)

The measurement scales were adapted from established studies to ensure content validity and theoretical consistency. Minor modifications were made to the wording of certain items to align them with the objectives of the study and the context of digital platform usage. Following data collection, the measurement instrument was subjected to Exploratory Factor Analysis (EFA) and subsequently evaluated through Partial Least Squares Structural Equation Modelling (PLS-SEM) to assess reliability, validity, and structural relationships among the constructs.

3.8.1 Degree of Digital Access (DA)

Degree of Digital Access refers to the extent to which individuals have access to digital devices, internet connectivity, and digital services. The construct captures the availability and accessibility of technological resources that facilitate participation in digital environments. The conceptualization of digital access is derived from the digital divide literature. Hargittai (2002) emphasized differences in individuals' ability to access and utilize digital technologies, while Van Dijk (2006) highlighted access as a fundamental determinant of digital participation. In the present study, Digital Access was measured using five items assessing respondents' access to internet-enabled devices, connectivity, and digital services.

3.8.2 Screen Usage Intensity (SUI)

Screen Usage Intensity refers to the frequency, duration, and extent of engagement with digital screens and online platforms. The construct reflects patterns of digital consumption across activities such as social networking, communication, entertainment, and information access. Ellison et al. (2007) and Junco (2012) employed intensity-based

measures to examine user engagement with digital platforms. Accordingly, Screen Usage Intensity was measured using nine items assessing the frequency and duration of respondents' digital activities.

3.8.3 Screen Addiction (SA)

Screen Addiction refers to compulsive and excessive engagement with digital devices characterized by impaired self-control, preoccupation, and difficulty reducing usage despite negative consequences. The construct is grounded in Behavioural Addiction Theory and draws upon established measures of internet and smartphone addiction. Young (1998) conceptualized problematic internet use as a behavioural disorder, while Kwon et al. (2013) developed validated measures of smartphone addiction. In the present study, Screen Addiction was measured using nine items capturing compulsive digital engagement and behavioural dependence.

3.8.4 Productivity Loss (PL)

Productivity Loss refers to reductions in efficiency, concentration, task completion, and effective time management resulting from excessive digital engagement. Existing research has shown that digital distractions and frequent interruptions can adversely affect cognitive performance and workplace productivity. Mark et al. (2015) examined the consequences of interruptions on work performance, whereas Duke and Montag (2017) highlighted the behavioural implications of excessive smartphone use. The construct was measured using nine items assessing the extent to which digital engagement interfered with respondents' productivity and task performance.

3.8.5 Mental Hygiene Issues (MHI)

Mental Hygiene Issues refer to adverse psychological outcomes associated with excessive digital engagement, including reduced psychological well-being, emotional exhaustion, diminished autonomy, and difficulties in maintaining positive mental functioning. The construct is informed by the psychological well-being framework developed by Ryff (1989) and subsequent well-being measures proposed by Diener et al. (2010). In the present study, Mental Hygiene Issues were measured using fifteen items assessing various dimensions of psychological functioning and emotional well-being.

3.8.6 Asymmetric Information (AS)

Asymmetric Information refers to situations in which digital platforms possess substantially greater knowledge regarding data collection practices, algorithmic processes, behavioural targeting mechanisms, and engagement optimization strategies than users. The theoretical foundation of the construct can be traced to Akerlof's (1970) Information Asymmetry Theory, which explains how unequal access to information can generate inefficient outcomes. More recent studies by Acquisti et al. (2015) and Zuboff (2019) highlighted the growing information imbalance between digital platforms and

users. In the present study, Asymmetric Information was measured using nine items assessing respondents' perceptions of transparency, awareness, and understanding of platform practices.

3.9 Data Analysis Technique

The data collected for the present study were analysed using IBM SPSS Statistics and SmartPLS 4. The analysis was conducted in two stages. Initially, Exploratory Factor Analysis (EFA) was performed using SPSS to examine the underlying factor structure of the measurement items and establish preliminary construct validity. Subsequently, Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed using SmartPLS 4 to evaluate the measurement model and test the proposed structural relationships.

EFA was considered appropriate because the measurement instrument consisted of multiple items adapted from different theoretical and empirical sources. The technique facilitated the identification of latent dimensions, assessment of factor loadings, and refinement of the measurement instrument through the removal of indicators exhibiting low factor loadings or substantial cross-loadings. This process improved construct clarity and strengthened the validity of the measurement scales.

Following EFA, the refined set of indicators was analysed using PLS-SEM. Hair et al. (2022) stated that PLS-SEM is particularly suitable for predictive and explanatory research involving multiple latent constructs, complex structural relationships, and moderation effects. The technique was considered appropriate for the present study because the proposed model comprises multiple endogenous and exogenous constructs and seeks to examine both direct and moderating relationships simultaneously.

The analysis proceeded through two major stages. The first stage involved the assessment of the measurement model through indicator reliability, internal consistency reliability, convergent validity, discriminant validity, and multicollinearity diagnostics. The second stage involved the evaluation of the structural model through path coefficient estimation, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and hypothesis testing.

The statistical significance of the hypothesized relationships was examined using the bootstrapping procedure in SmartPLS 4. In addition, moderation analysis was conducted to assess the moderating effect of Asymmetric Information (AS) on the relationships between Digital Access (DA) and Screen Use Intensity (SUI), and between Digital Access (DA) and Screen Addiction (SA). The results of these analyses provided the empirical basis for evaluating the proposed conceptual framework and testing the study hypotheses.

3.10 Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis (EFA) was conducted as a preliminary stage of data analysis to examine the dimensionality of the measurement instrument and refine the measurement scales before structural model estimation. Since the questionnaire items were

adapted from multiple theoretical and empirical sources, it was necessary to verify whether the indicators adequately represented their intended constructs. EFA therefore served as a scale purification procedure by identifying the underlying factor structure, evaluating indicator performance, and removing problematic items prior to measurement model assessment.

3.10.1 Assessment of Data Suitability

Prior to factor extraction, the suitability of the dataset was evaluated using the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. Kaiser (1974) suggested that KMO values above 0.60 indicate acceptable sampling adequacy, while values above 0.80 indicate strong suitability for factor analysis.

Bartlett's Test of Sphericity was employed to determine whether the correlation matrix differed significantly from an identity matrix. Bartlett (1954) stated that a statistically significant result ($p < 0.05$) indicates sufficient intercorrelations among variables and supports the application of factor analysis.

3.10.2 Factor Extraction

Following confirmation of data suitability, factor extraction was performed using Principal Component Analysis (PCA). Hair et al. (2019) noted that PCA is widely used for scale purification and data reduction in behavioural and social science research.

Factors were retained using Kaiser's (1960) criterion, whereby only factors with eigenvalues greater than one were considered for further analysis. In addition to statistical criteria, the theoretical interpretability of the extracted factors was also considered during factor retention.

3.10.3 Rotation Method

To obtain a clearer and more interpretable factor structure, Varimax Rotation with Kaiser Normalization was employed. Hair et al. (2019) explained that Varimax rotation maximises the variance of factor loadings and improves the distinction between factors, thereby facilitating interpretation.

The rotated solution enabled clearer identification of indicators associated with their respective constructs and reduced overlap among factors.

3.10.4 Assessment of Factor Loadings

The rotated factor loading matrix was examined to evaluate the contribution of individual indicators to their respective latent constructs. Following the recommendations of Hair et al. (2019), a minimum loading threshold of 0.50 was adopted for item retention.

Indicators exhibiting strong loadings on their intended factor and relatively weak loadings on other factors were considered evidence of satisfactory construct representation.

3.10.5 Item Deletion Criteria

The measurement instrument was refined through an iterative review of factor loadings, cross-loadings, and theoretical relevance. Indicators were considered for removal if they exhibited factor loadings below 0.50, substantial cross-loadings on multiple factors, or weak conceptual alignment with the construct they were intended to measure.

While statistical criteria guided item purification, theoretical considerations were also taken into account to preserve construct meaning and ensure conceptual consistency. The refined set of indicators was retained for subsequent measurement model assessment and structural model analysis.

3.10.6 Communality Assessment

Communality values were examined to determine the proportion of variance in each indicator explained by the extracted factors. Hair et al. (2019) suggested that communality values above 0.40 generally indicate that an indicator contributes adequately to the factor structure.

Indicators with low communalities were reviewed carefully to ensure that only meaningful and representative measures were retained in the final instrument.

The refined factor structure obtained through EFA provided the basis for subsequent measurement model assessment, including reliability and validity evaluation, before proceeding to structural model analysis using PLS-SEM.

3.11 Measurement Model Assessment

Following the refinement of the measurement instrument through Exploratory Factor Analysis (EFA), the measurement model was evaluated using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4. Measurement model assessment was undertaken to determine whether the observed indicators adequately represented their respective latent constructs and whether the constructs demonstrated satisfactory levels of reliability and validity. Hair et al. (2022) emphasized that establishing an acceptable measurement model is a prerequisite for structural model evaluation and hypothesis testing.

The assessment focused on indicator reliability, internal consistency reliability, convergent validity, discriminant validity, and multicollinearity diagnostics.

3.11.1 Indicator Reliability

Indicator reliability was assessed through outer loadings generated by the PLS algorithm. Outer loadings indicate the extent to which an indicator is explained by its underlying construct. Hair et al. (2022) suggested that loadings of 0.708 or higher are desirable, as they indicate that the construct explains at least 50 percent of the indicator variance. Indicators with loadings between 0.40 and 0.70 may be retained if supported by theoretical considerations and if their removal does not improve construct quality substantially.

3.11.2 Internal Consistency Reliability

Internal consistency reliability evaluates whether the indicators associated with a construct consistently measure the same underlying concept. Reliability was assessed using Cronbach's Alpha, Composite Reliability (CR), and rho_A.

Cronbach's Alpha

Cronbach's Alpha measures the degree of consistency among indicators within a construct. Nunnally and Bernstein (1994) suggested that values of 0.70 or higher indicate acceptable reliability, while values above 0.80 indicate good reliability.

Composite Reliability (CR)

Composite Reliability is generally preferred in PLS-SEM because it accounts for differences in indicator loadings and provides a more accurate estimate of construct reliability. Hair et al. (2022) recommended values between 0.70 and 0.95 as satisfactory.

rho_A

Dijkstra and Henseler (2015) proposed rho_A as a consistent reliability measure for variance-based structural equation modelling. Values of 0.70 or above indicate acceptable construct reliability.

3.11.3 Convergent Validity

Convergent validity assesses the extent to which indicators associated with a construct converge in measuring the same underlying concept. It was evaluated using the Average Variance Extracted (AVE).

Average Variance Extracted (AVE)

Fornell and Larcker (1981) stated that AVE values of 0.50 or higher indicate satisfactory convergent validity, implying that the construct explains at least half of the variance of its indicators.

3.11.4 Discriminant Validity

Discriminant validity examines whether a construct is empirically distinct from other constructs included in the model. The assessment was conducted using the Fornell-Larcker Criterion and the Heterotrait-Monotrait Ratio (HTMT).

Fornell-Larcker Criterion

According to Fornell and Larcker (1981), the square root of a construct's AVE should exceed its correlations with all other constructs. This indicates that the construct shares more variance with its own indicators than with other constructs in the model.

Heterotrait-Monotrait Ratio (HTMT)

Henseler et al. (2015) recommended HTMT as a more rigorous assessment of discriminant validity. HTMT values below 0.85 indicate satisfactory discriminant validity, while values below 0.90 may be acceptable for conceptually related constructs.

3.11.5 Assessment of Multicollinearity

Multicollinearity was assessed using the Variance Inflation Factor (VIF). Hair et al. (2022) suggested that VIF values below 5.0 indicate the absence of critical multicollinearity concerns, while values below 3.3 are generally considered preferable.

The establishment of satisfactory reliability, validity, and collinearity diagnostics provided the basis for evaluating the structural model and testing the proposed hypotheses.

3.12 Structural Model Assessment

Following the establishment of reliability and validity of the measurement model, the structural model was evaluated to examine the hypothesized relationships among the latent constructs. Hair et al. (2022) stated that structural model assessment enables researchers to evaluate the explanatory and predictive capability of a model and determine whether the proposed theoretical relationships are supported by empirical evidence.

The structural model was assessed through path coefficients, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), bootstrapping, mediation analysis, and moderation analysis.

3.12.1 Path Coefficients

Path coefficients were examined to assess the strength and direction of the relationships among the constructs included in the model. In PLS-SEM, path coefficients represent standardized regression estimates and indicate the extent to which changes in one construct influence another while controlling for the effects of other variables.

The statistical significance of the path coefficients was assessed using bootstrapping. Following Hair et al. (2022) and Field (2018), relationships were considered statistically significant when the associated p-value was less than 0.05 and the corresponding t-value exceeded 1.96 in a two-tailed test.

3.12.2 Coefficient of Determination (R^2)

The coefficient of determination (R^2) was used to evaluate the explanatory power of the model. R^2 represents the proportion of variance in an endogenous construct explained by its predictor constructs. Hair et al. (2022) suggested that values of approximately 0.25, 0.50, and 0.75 may be interpreted as weak, moderate, and substantial explanatory power, respectively.

3.12.3 Effect Size (f^2)

Effect size (f^2) was assessed to determine the contribution of individual predictor constructs to endogenous constructs. Cohen (1988) suggested that f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively.

3.12.4 Predictive Relevance (Q^2)

Predictive relevance was evaluated using Stone-Geisser's Q^2 statistic obtained through the blindfolding procedure. Stone (1974) and Geisser (1974) proposed that Q^2 values greater than zero indicate that a model possesses predictive relevance for a given endogenous construct.

3.12.5 Bootstrapping Procedure

The significance of the structural relationships was evaluated using the bootstrapping procedure available in SmartPLS 4. Following the recommendations of Hair et al. (2022), 5,000 bootstrap resamples were generated to estimate standard errors, confidence intervals, t-statistics, and p-values.

A relationship was considered statistically significant when:

- p-value < 0.05;
- t-value > 1.96 (two-tailed test);
- the confidence interval did not include zero.

3.12.6 Mediation Analysis

Mediation analysis was conducted to examine whether Screen Use Intensity (SUI) and Screen Addiction (SA) function as intervening mechanisms through which Digital Access (DA) influences Impact on Productivity (IP) and Mental Hygiene (MH).

The assessment was based on the significance of indirect effects obtained through bootstrapping. Following Zhao et al. (2010) and Hair et al. (2022), mediation was considered present when the indirect effect was statistically significant.

The nature of mediation was interpreted as follows:

- Full Mediation: Significant indirect effect and non-significant direct effect;
- Partial Mediation: Significant indirect effect and significant direct effect;
- No Mediation: Non-significant indirect effect.

3.12.7 Moderation Analysis

Moderation analysis was conducted to examine whether Asymmetric Information (AS) influences the relationship between Digital Access (DA) and behavioural outcomes. Moderating effects were assessed through interaction terms generated in SmartPLS 4.

The significance of the interaction effects was evaluated using bootstrapped path coefficients, t-values, and p-values. A statistically significant interaction coefficient indicated the presence of moderation, whereas a non-significant coefficient indicated that the relationship remained stable across different levels of the moderator.

The successful assessment of the structural model provided the basis for hypothesis testing and evaluation of the proposed conceptual framework.

3.13 Conclusion

This chapter presented the methodological framework adopted for the study. It outlined the research philosophy, research approach, research design, population, sampling procedure, data collection process, measurement instrument, and operationalization of the study variables. A quantitative research methodology based on the positivist paradigm and deductive approach was employed to empirically examine the proposed conceptual framework.

The chapter also discussed the procedures used for data analysis. Exploratory Factor Analysis (EFA) was undertaken to assess the dimensionality of the measurement instrument and refine the measurement scales. Subsequently, Partial Least Squares Structural Equation Modelling (PLS-SEM) was adopted to evaluate the measurement model and test the hypothesized relationships among the constructs. The criteria for assessing reliability, validity, explanatory power, predictive relevance, mediation effects, and moderation effects were also specified.

The methodological procedures outlined in this chapter provide the foundation for the empirical analysis presented in the subsequent chapter. Chapter 4 reports the results of the data analysis and presents the findings obtained from EFA and PLS-SEM.

Chapter 4

Data Analysis and Interpretation

4.1 Introduction

This chapter presents the empirical analysis and interpretation of the data collected for the study. The analysis was conducted using IBM SPSS Statistics and SmartPLS 4 in accordance with the methodological framework outlined in Chapter 3.

The chapter begins with an examination of the demographic profile of the respondents, followed by the results of Exploratory Factor Analysis (EFA) conducted to assess the dimensionality of the measurement instrument. Subsequently, the measurement model is evaluated through indicator reliability, internal consistency reliability, convergent validity, discriminant validity, and multicollinearity assessment.

After establishing the adequacy of the measurement model, the structural model is assessed to examine the proposed relationships among Digital Access (DA), Screen Use Intensity (SUI), Screen Addiction (SA), Impact on Productivity (IP), Mental Hygiene (MH), and Asymmetric Information (AS). The chapter further presents the results of hypothesis testing, explanatory power assessment, predictive relevance evaluation, mediation analysis, and moderation analysis.

The findings reported in this chapter provide empirical evidence regarding the relationships among the study constructs and serve as the basis for the discussion and interpretation of results presented in the subsequent chapter.

4.2 Profile of Respondents

This section presents the demographic and digital engagement characteristics of the respondents included in the study. Profile analysis provides an overview of the composition of the sample and helps establish the suitability of the respondents for examining the proposed research framework. The analysis focuses on age distribution, primary activity, screen time patterns, and social media usage.

4.2.1 Age Distribution

Table 4.1 presents the age distribution of the respondents included in the study.

Table 4.1: Age Distribution of Respondents

Age Group	Frequency	Percentage (%)
Below 20 Years	83	47.7
21–30 Years	75	43.1
31–40 Years	15	8.6
Above 40 Years	1	0.6
Total	174	100.0

Table 4.1 indicates that the respondent pool is predominantly concentrated in the younger age categories. Respondents below 20 years of age constitute the largest segment of the sample, accounting for 47.7 percent of the total respondents, followed by those aged 21–30 years, who represent 43.1 percent of the sample. In contrast, respondents above 30 years account for only 9.2 percent of the total sample.

Overall, approximately 90.8 percent of the respondents fall within the age range of below 30 years, indicating a strong representation of younger individuals. This distribution is appropriate for the present study, as younger age groups are generally characterised by higher levels of internet usage, smartphone ownership, social media participation, and engagement with digital platforms. Consequently, the sample provides a suitable basis for examining patterns of digital engagement and their behavioural outcomes.

4.2.2 Primary Activity of Respondents

To capture variation in digital engagement across different population groups, the study included school students, college and university students, and working professionals. Table 4.2 presents the distribution of respondents according to their primary activity.

Table 4.2: Primary Activity of Respondents

Primary Activity	Frequency	Percentage (%)
School Students	37	21.3
College/University Students	93	53.4
Working Professionals	44	25.3
Total	174	100.0

Table 4.2 shows that college and university students constitute the largest segment of the sample, representing 53.4 percent of the respondents. Working professionals account for 25.3 percent, while school students comprise 21.3 percent of the sample. Collectively, students (school and college/university) represent 74.7 percent of the respondents, indicating a strong representation of individuals who are regularly exposed to digital technologies for educational, social, and recreational purposes.

The distribution is consistent with the objectives of the study, as students and young adults are among the most active users of smartphones, social media platforms, online learning systems, and digital communication tools. At the same time, the inclusion of working professionals broadens the scope of the analysis by incorporating respondents

who rely on digital technologies for occupational and professional activities. This composition enhances the relevance of the sample for examining behavioural patterns associated with digital engagement across different user groups.

4.2.3 Average Daily Screen Time across Respondent Categories

To examine patterns of digital engagement across different respondent groups, average daily screen time was analysed for school students, college and university students, and working professionals. The results are presented in Table 4.3.

Table 4.3: Average Daily Screen Time by Primary Activity

Primary Activity	Frequency	Average Daily Screen Time (Hours)
School Students	37	11.33
College/University Students	93	9.32
Working Professionals	44	9.69
Total	174	9.84

Table 4.3 indicates that school students reported the highest average daily screen time, with an average of 11.33 hours per day. This level of exposure may reflect the combined use of digital devices for educational activities, entertainment, social networking, gaming, and content consumption. Working professionals reported an average screen time of 9.69 hours per day, while college and university students recorded an average of 9.32 hours per day.

Although variations exist across respondent categories, all three groups reported substantial daily screen exposure. The overall average screen time of 9.84 hours per day suggests a high level of interaction with digital technologies among the respondents. Such extensive digital engagement indicates that the sample is well suited for examining the relationships between digital access, screen use intensity, screen addiction, impact on productivity, and mental hygiene.

4.2.4 Summary of Respondent Characteristics

The demographic profile indicates that the sample is predominantly composed of young and digitally active individuals. More than ninety percent of respondents are below the age of 30 years, and nearly three-fourths are students. In addition, respondents across all categories reported substantial levels of daily screen exposure, highlighting the central role of digital technologies in their daily activities.

The inclusion of school students, college and university students, and working professionals ensures representation of diverse user groups with varying patterns of technology use. Collectively, these characteristics suggest that the sample provides an appropriate basis for examining digital engagement behaviours and their associated outcomes within the proposed research framework.

4.3 Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis (EFA) was conducted to examine the dimensionality of the measurement instrument and refine the measurement scales prior to measurement model assessment. As the questionnaire items were adapted from multiple theoretical and empirical sources, EFA was employed to verify the underlying factor structure and ensure that the indicators adequately represented their intended constructs. The analysis was performed using Principal Component Analysis (PCA) with Varimax Rotation in IBM SPSS Statistics.

4.3.1 KMO and Bartlett's Test

Prior to factor extraction, the suitability of the dataset was assessed using the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. The results are presented in Table 4.4.

Table 4.4: KMO and Bartlett's Test

Measure	Value
Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy	0.899
Bartlett's Test of Sphericity (Approx. Chi-Square)	5211.043
Degrees of Freedom (df)	741
Significance (p-value)	0.000

Table 4.4 indicates a KMO value of 0.899, which exceeds the recommended threshold of 0.60 and falls within the category of excellent sampling adequacy as suggested by Kaiser (1974). This result indicates that the variables share sufficient common variance and are appropriate for factor analysis.

Bartlett's Test of Sphericity was statistically significant ($\chi^2 = 5211.043$, $p < 0.001$), indicating that the correlation matrix differs significantly from an identity matrix. The result confirms the existence of sufficient intercorrelations among the variables to justify factor extraction.

Overall, the findings demonstrate that the dataset satisfies the statistical requirements for Exploratory Factor Analysis and provides a robust foundation for identifying the underlying factor structure of the measurement instrument.

4.3.2 Factor Extraction

Following confirmation of the suitability of the dataset, factor extraction was performed using Principal Component Analysis (PCA). The objective of this stage was to identify the underlying dimensions represented by the survey items and determine whether the observed variables clustered in a manner consistent with the proposed construct structure.

The number of factors retained was determined using Kaiser's criterion. Kaiser (1960) suggested that only factors with eigenvalues greater than one should be retained for further analysis. The results of the factor extraction are presented in Table 4.5.

Table 4.5: Initial Eigenvalues and Variance Explained

Component	Eigenvalue	Percentage of Variance Explained (%)	Cumulative Variance (%)
1	13.554	34.754	34.754
2	5.374	13.780	48.534
3	3.156	8.092	56.626
4	1.886	4.837	61.463
5	1.604	4.113	65.576
6	1.336	3.425	69.001

Source: Author's computation using SPSS 27.

The analysis identified six factors with eigenvalues exceeding the threshold value of one. Collectively, these factors accounted for 69.001 percent of the total variance in the dataset. Hair et al. (2019) noted that, in social science research, a cumulative variance explained of 60 percent or higher is generally considered satisfactory. The extracted variance therefore indicates that the retained factors capture a substantial proportion of the information contained in the original set of variables.

An examination of the eigenvalues reveals that the first factor explained 34.754 percent of the total variance, representing the largest share of variability in the dataset. The second factor contributed an additional 13.780 percent, increasing the cumulative variance explained to 48.534 percent. The remaining four factors collectively accounted for approximately 20.5 percent of the total variance, resulting in a cumulative variance explained of 69.001 percent.

The retention of six factors is consistent with the proposed measurement structure of the study, comprising Digital Access (DA), Screen Use Intensity (SUI), Asymmetric Information (AS), Screen Addiction (SA), Mental Hygiene (MH), and Impact on Productivity (IP). The factor extraction results therefore provide preliminary empirical support for the multidimensional structure of the measurement instrument and justify further examination of the factor solution through rotation and factor loading analysis.

4.3.3 Scree Plot Analysis

In addition to Kaiser's eigenvalue criterion, the scree plot was examined to determine the appropriate number of factors to retain. The scree plot provides a graphical representation of the eigenvalues associated with the extracted components and assists in identifying the point at which additional factors contribute only marginally to the explanation of variance. This procedure, commonly referred to as the Scree Test, was proposed by Cattell (1966). Figure 4.1 shows a steep decline in eigenvalues across the first six components, followed by a clear flattening of the curve. The elbow of the scree plot occurs after the sixth component, indicating that additional factors contribute relatively little to the explanation of total variance. The scree plot therefore supports the retention of six factors, consistent with the results obtained using Kaiser's criterion. The convergence of evidence from both approaches provides additional support for the six-factor structure adopted for subsequent analyses.

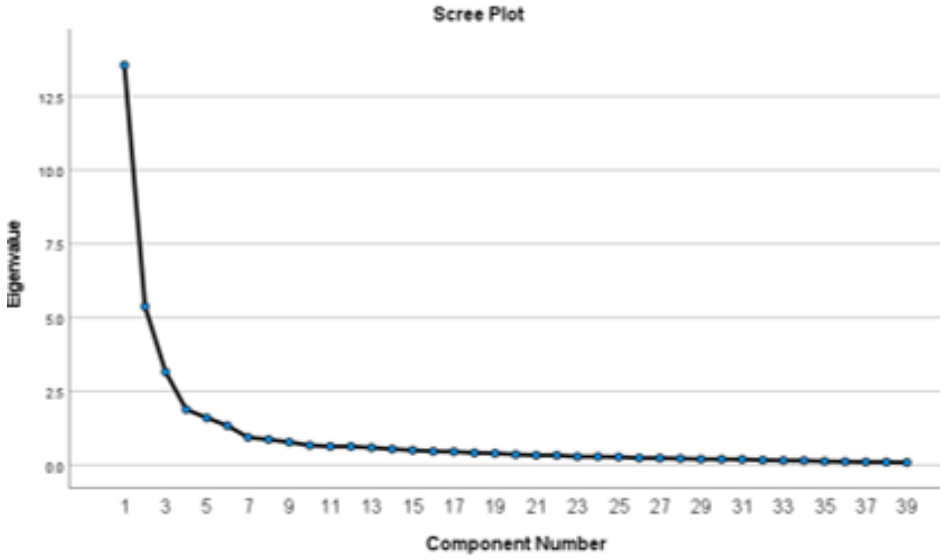


Figure 4.1: Scree Plot of Extracted Components

4.3.4 Rotated Component Matrix

To obtain a clearer and more interpretable factor structure, Varimax Rotation with Kaiser Normalization was applied to the extracted factors. Rotation improves factor interpretability by maximising high loadings and minimising low loadings across factors. The rotated component matrix is presented in Table 4.6.

4.3.5 Rotated Component Matrix

To obtain a clearer and more interpretable factor structure, Varimax Rotation with Kaiser Normalization was applied to the extracted factors. Rotation improves factor interpretability by maximising high loadings and minimising low loadings across factors, thereby facilitating the identification of meaningful relationships between indicators and their underlying constructs. The rotated component matrix is presented in Table 4.6. The rotated solution converged successfully after six iterations and produced a well-defined six-factor structure. All retained indicators exhibited factor loadings above the recommended threshold of 0.50 suggested by Hair et al. (2019), indicating satisfactory associations between the indicators and their respective latent constructs. Furthermore, no substantial cross-loadings were observed, suggesting that the indicators demonstrated clear construct membership and adequate discriminant properties.

Table 4.6: Rotated Component Matrix

Indicator	Component 1	Component 2	Component 3	Component 4	Component 5	Component 6
DA1						0.807
DA2						0.821
DA3						0.660
SUI3(d1)			0.672			
SUI4(d2)			0.792			
SUI5(d2)			0.786			
SUI6(d2)			0.779			
SUI7(d3)			0.638			
SUI8(d3)			0.603			
AS4(d2)				0.667		
AS5(d2)				0.758		
AS6(d2)				0.739		
AS7(d3)				0.717		
AS8(d3)				0.772		
AS9(d3)				0.627		
SA2(d1)					0.581	
SA3(d1)					0.681	
SA4(d2)					0.747	
SA5(d2)					0.717	
SA6(d2)					0.540	
SA7(d3)					0.679	
SA8(d3)					0.603	
MH1(d1)		0.642				
MH4(d1)		0.765				
MH5(d1)		0.802				
MH6(d2)		0.768				
MH8(d2)		0.861				
MH10(d2)		0.806				
MH11(d3)		0.816				
MH12(d3)		0.811				
IP1(d1)	0.633					
IP2(d1)	0.745					
IP3(d1)	0.765					
IP4(d2)	0.733					
IP5(d2)	0.819					
IP6(d2)	0.815					
IP7(d3)	0.850					
IP8(d3)	0.865					
IP9(d3)	0.808					

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 6 iterations. Only retained indicators are reported.

The first factor comprised the indicators associated with Impact on Productivity (IP), with loadings ranging from 0.633 to 0.865. The second factor captured Mental Hygiene (MH), where factor loadings ranged from 0.642 to 0.861. The third factor represented Screen Use Intensity (SUI), with loadings between 0.603 and 0.792. The fourth factor corresponded to Asymmetric Information (AS), exhibiting loadings ranging from 0.627 to 0.772.

The fifth factor reflected Screen Addiction (SA), with factor loadings varying between 0.540 and 0.747. Although some indicators displayed comparatively lower loadings, all exceeded the minimum retention criterion and were therefore retained for subsequent analysis. The sixth factor represented Digital Access (DA), with loadings ranging from 0.660 to 0.821, indicating satisfactory representation of the construct.

Importantly, the empirical factor structure closely aligned with the conceptual framework developed in Chapter 2. The six factors extracted through EFA corresponded directly to the six constructs proposed in the study, namely Digital Access (DA), Screen Use Intensity (SUI), Asymmetric Information (AS), Screen Addiction (SA), Mental Hygiene (MH), and Impact on Productivity (IP). This correspondence provides preliminary evidence of construct validity and supports the theoretical structure underlying the measurement instrument.

Overall, the rotated component matrix demonstrates a stable and interpretable factor solution characterised by strong factor loadings, limited cross-loadings, and clear separation among constructs. The results therefore support the suitability of the refined measurement instrument for subsequent reliability, validity, and structural model assessment using PLS-SEM.

The rotated solution converged successfully after six iterations and produced a well-defined six-factor structure. All retained indicators exhibited factor loadings above the recommended threshold of 0.50 suggested by Hair et al. (2019), indicating satisfactory associations between the indicators and their respective latent constructs. Furthermore, no substantial cross-loadings were observed, suggesting that the indicators demonstrated clear construct membership and adequate discriminant properties.

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Overall, the rotated component matrix demonstrates a stable and interpretable factor solution characterised by strong factor loadings, limited cross-loadings, and clear separation among constructs. The results therefore support the suitability of the refined measurement instrument for subsequent reliability, validity, and structural model assessment using PLS-SEM.

4.3.6 Communality Assessment

Following factor extraction and rotation, communality values were examined to assess the extent to which each indicator was represented by the retained factor structure. Communality indicates the proportion of variance in an observed variable explained by the extracted factors. Higher values suggest that an indicator is adequately represented within the factor solution and contributes meaningfully to the measurement model (Hair et al., 2019).

Table 4.7: Communality Values

Indicator	Initial	Extraction
DA1	1.000	0.745
DA2	1.000	0.799
DA3	1.000	0.672
SUI3(d1)	1.000	0.647
SUI4(d2)	1.000	0.689
SUI5(d2)	1.000	0.713
SUI6(d2)	1.000	0.670
SUI7(d3)	1.000	0.594
SUI8(d3)	1.000	0.535
AS4(d2)	1.000	0.621
AS5(d2)	1.000	0.704
AS6(d2)	1.000	0.682
AS7(d3)	1.000	0.686
AS8(d3)	1.000	0.748
AS9(d3)	1.000	0.546
SA2(d1)	1.000	0.713
SA3(d1)	1.000	0.732
SA4(d2)	1.000	0.755
SA5(d2)	1.000	0.781
SA6(d2)	1.000	0.644
SA7(d3)	1.000	0.679
SA8(d3)	1.000	0.620
MH1(d1)	1.000	0.616
MH4(d1)	1.000	0.700
MH5(d1)	1.000	0.723
MH6(d2)	1.000	0.638
MH8(d2)	1.000	0.757
MH10(d2)	1.000	0.668
MH11(d3)	1.000	0.688
MH12(d3)	1.000	0.701
IP1(d1)	1.000	0.596
IP2(d1)	1.000	0.705
IP3(d1)	1.000	0.727

Continued on next page

Table 4.7 – Continued from previous page

Indicator	Initial	Extraction
IP4(d2)	1.000	0.706
IP5(d2)	1.000	0.737
IP6(d2)	1.000	0.732
IP7(d3)	1.000	0.761
IP8(d3)	1.000	0.780
IP9(d3)	1.000	0.701

Source: Author's computation using IBM SPSS Statistics.

The communality values presented in Table 4.7 range from 0.535 to 0.799. Hair et al. (2019) suggested that communality values above 0.40 indicate adequate representation of indicators within the extracted factor structure. All retained indicators exceeded this threshold, confirming that each item was satisfactorily explained by the six-factor solution.

The highest communality value was observed for DA2 (0.799), indicating that approximately 79.9 percent of its variance was explained by the retained factors. Conversely, SUI8 recorded the lowest communality value (0.535); however, it remained well above the recommended threshold and was therefore retained. Notably, the majority of indicators exhibited communality values greater than 0.60, suggesting that the extracted factors accounted for a substantial proportion of item variance.

Overall, the communality assessment provides additional evidence regarding the adequacy of the factor solution and confirms that the retained indicators are appropriately represented by their respective latent constructs. These findings support the use of the refined measurement instrument for subsequent reliability, validity, and structural model assessment using PLS-SEM.

4.3.7 Conclusion of EFA

The Exploratory Factor Analysis (EFA) provided empirical support for the dimensional structure of the measurement instrument. The KMO value of 0.899 and the statistically significant Bartlett's Test of Sphericity confirmed the suitability of the dataset for factor analysis. Principal Component Analysis identified six factors with eigenvalues greater than one, collectively explaining 69.001 percent of the total variance.

The six-factor solution was further supported by the scree plot and the rotated component matrix, which revealed strong factor loadings, satisfactory communality values, and minimal cross-loadings among indicators. The extracted factors aligned closely with the proposed construct structure comprising Digital Access (DA), Screen Use Intensity (SUI), Asymmetric Information (AS), Screen Addiction (SA), Mental Hygiene (MH), and Impact on Productivity (IP).

Following the purification process, 39 indicators were retained for further analysis. All retained items satisfied the recommended thresholds for factor loadings and communalities, indicating adequate representation of their respective constructs.

Overall, the EFA results confirm the adequacy of the refined measurement instrument and provide preliminary evidence of construct validity. The retained indicators

were therefore considered suitable for subsequent measurement model assessment and structural model evaluation using PLS-SEM.

4.4 Measurement Model Assessment

Following the exploratory factor analysis, the measurement model was assessed using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4. The objective of this stage was to evaluate the reliability and validity of the retained constructs before examining the structural relationships proposed in the conceptual framework. The assessment involved evaluating indicator reliability, internal consistency reliability, convergent validity, discriminant validity, and multicollinearity.

4.4.1 Indicator Reliability

Indicator reliability was assessed through the examination of outer loadings. Outer loadings indicate the strength of the relationship between an indicator and its corresponding latent construct. Hair et al. (2022) suggested that outer loadings of 0.708 or higher are generally desirable, as they indicate that the construct explains more than 50 percent of the variance in the indicator.

Table 4.8: Summary of Outer Loadings

Construct	Range of Outer Loadings	Assessment
Digital Access (DA)	0.811 – 0.895	Satisfactory
Screen Use Intensity (SUI)	0.754 – 0.819	Satisfactory
Asymmetric Information (AS)	0.737 – 0.857	Satisfactory
Screen Addiction (SA)	0.770 – 0.879	Satisfactory
Mental Hygiene (MH)	0.682 – 0.874	Acceptable
Impact on Productivity (IP)	0.742 – 0.862	Satisfactory

Source: Author's computation using SmartPLS 4.

The results indicate that the retained indicators exhibited satisfactory levels of reliability across all constructs. The outer loadings for Digital Access ranged from 0.811 to 0.895, while the indicators measuring Asymmetric Information recorded loadings between 0.737 and 0.857. Similarly, the loadings for Screen Use Intensity and Screen Addiction ranged from 0.754 to 0.819 and 0.770 to 0.879, respectively.

The Mental Hygiene construct exhibited loadings ranging from 0.682 to 0.874. Although one indicator (MH1) recorded a loading slightly below the recommended threshold of 0.708, it was retained due to its theoretical relevance and because the construct demonstrated satisfactory reliability and validity overall. The indicators associated with Impact on Productivity exhibited strong loadings ranging from 0.742 to 0.862.

Overall, the outer loading values exceeded the minimum acceptable threshold and demonstrated strong relationships between the indicators and their respective latent

constructs. Therefore, indicator reliability was considered satisfactory, supporting the adequacy of the measurement model for further reliability and validity assessment.

4.4.2 Internal Consistency Reliability and Convergent Validity

Following the assessment of indicator reliability, the internal consistency and convergent validity of the constructs were evaluated. Internal consistency reliability examines the extent to which the indicators associated with a construct consistently measure the same underlying concept, whereas convergent validity assesses whether the indicators of a construct share a high proportion of common variance. In PLS-SEM, these properties are commonly evaluated using Cronbach's Alpha, Composite Reliability (ρ_c), rho_A, and Average Variance Extracted (AVE). The results are presented in Table **??**.

Table 4.9: Reliability and Convergent Validity Assessment

Construct	**Cronbach's Alpha**	ρ_A	ρ_C	**AVE**
Asymmetric Information	0.887	0.889	0.914	0.639
Digital Access	0.832	0.863	0.898	0.747
Impact on Productivity	0.944	0.946	0.952	0.690
Mental Hygiene	0.921	0.969	0.934	0.639
Screen Addiction	0.922	0.925	0.937	0.681
Screen Use Intensity	0.895	0.899	0.917	0.614

Source: Author's computation using SmartPLS 4.

Source: Author's computation using SmartPLS 4.

The results indicate strong internal consistency across all constructs. Cronbach's Alpha values range from 0.832 to 0.944, exceeding the recommended threshold of 0.70 suggested by Nunnally and Bernstein (1994). Similarly, Composite Reliability values range from 0.898 to 0.952, while rho_A values range from 0.863 to 0.969. All values comfortably exceed the recommended minimum level of 0.70, indicating that the retained indicators consistently measure their respective latent constructs (Hair et al., 2022).

Convergent validity was assessed using the Average Variance Extracted (AVE). According to Fornell and Larcker (1981), AVE values greater than 0.50 indicate that a construct explains more than half of the variance in its indicators. The AVE values obtained range from 0.614 to 0.747, demonstrating satisfactory convergent validity for all constructs. Digital Access recorded the highest AVE value (0.747), while Screen Use Intensity reported the lowest value (0.614). Nevertheless, all constructs exceeded the recommended threshold.

Overall, the results provide strong evidence of internal consistency reliability and convergent validity. The constructs demonstrate satisfactory reliability and adequately capture the variance of their respective indicators, thereby supporting the suitability of the measurement model for subsequent discriminant validity assessment and structural model evaluation.

4.4.3 Discriminant Validity

After establishing convergent validity, discriminant validity was assessed to determine whether the constructs included in the study were empirically distinct from one another. Consistent with current PLS-SEM recommendations, discriminant validity was evaluated using the Fornell-Larcker Criterion and the Heterotrait-Monotrait Ratio (HTMT) (Hair et al., 2022).

Fornell-Larcker Criterion

The Fornell-Larcker Criterion assesses discriminant validity by comparing the square root of the Average Variance Extracted (AVE) of each construct with its correlations with other constructs. Discriminant validity is established when the square root of AVE exceeds all corresponding inter-construct correlations (Fornell and Larcker, 1981).

Table 4.10: Fornell-Larcker Criterion

Construct	AS	DA	IP	MH	SA	SUI
AS	**0.799**					
DA	0.498	**0.864**				
IP	0.384	0.284	**0.831**			
MH	0.404	0.278	0.147	**0.799**		
SA	0.536	0.429	0.721	0.283	**0.825**	
SUI	0.549	0.490	0.425	0.262	0.598	**0.783**

Source: Author's computation using SmartPLS 4.

The results indicate that the square root of AVE for each construct exceeds its correlations with all other constructs. For example, Digital Access (0.864) exceeds its highest correlation with another construct (0.498), while Screen Addiction (0.825) exceeds its strongest correlation with Impact on Productivity (0.721). Similar patterns are observed across all constructs. Therefore, the Fornell-Larcker criterion is satisfied, providing evidence of discriminant validity.

Heterotrait-Monotrait Ratio (HTMT)

To provide a more rigorous assessment, discriminant validity was further evaluated using the Heterotrait-Monotrait Ratio (HTMT). Henseler et al. (2015) suggested that HTMT values below 0.85 indicate satisfactory discriminant validity. The HTMT values range from 0.039 to 0.768, all of which remain below the recommended threshold of 0.85. The highest value is observed between Screen Addiction and Impact on Productivity (0.768), indicating a relatively strong association while remaining within acceptable limits. The interaction construct (AS×DA) exhibits low HTMT values with all other constructs, confirming its empirical distinctiveness.

Table 4.11: HTMT Ratio

Construct	AS	DA	IP	MH	SA	SUI	AS×DA
AS							
DA	0.572						
IP	0.411	0.313					
MH	0.425	0.298	0.141				
SA	0.583	0.471	0.768	0.275			
SUI	0.607	0.550	0.454	0.257	0.652		
AS×DA	0.134	0.044	0.057	0.039	0.081	0.244	

Source: Author's computation using SmartPLS 4.

Taken together, the results of the Fornell-Larcker Criterion and HTMT analysis provide strong evidence of discriminant validity. The constructs are empirically distinct and suitable for subsequent structural model assessment.

4.4.4 Multicollinearity Assessment

In addition to reliability and validity assessment, multicollinearity was examined using the Variance Inflation Factor (VIF). Multicollinearity refers to excessive correlations among indicators, which may inflate standard errors and affect the stability of parameter estimates. Therefore, assessing VIF values is important to ensure the robustness of the measurement model.

According to Hair et al. (2022), VIF values below 5.0 indicate the absence of critical multicollinearity concerns, while values below 3.3 are generally considered desirable in behavioural research.

Table 4.12: Summary of VIF Values

Statistic	Value
Minimum VIF	1.000
Maximum VIF	3.495
Average VIF	2.44
Recommended Threshold	< 5.000

Source: Author's computation using SmartPLS 4.

The VIF values ranged from 1.000 to 3.495, indicating that all indicators fall well below the recommended threshold of 5.0. The highest VIF value was observed for SA5 (3.495), followed by IP8 (3.389) and IP6 (3.220). Although these values are relatively higher than those of the remaining indicators, they remain within acceptable limits and therefore do not indicate problematic collinearity.

The interaction construct (AS × DA) recorded a VIF value of 1.000, indicating the absence of multicollinearity concerns. Overall, the results suggest that the indicators provide unique information and do not exhibit excessive redundancy.

Consequently, multicollinearity is not a concern in the measurement model, supporting the stability and interpretability of the estimated parameters.

4.4.5 Summary of Measurement Model Results

The measurement model was evaluated through the assessment of indicator reliability, internal consistency reliability, convergent validity, discriminant validity, and multicollinearity. The results indicate that all constructs satisfied the recommended evaluation criteria.

Indicator reliability was established through satisfactory outer loadings, while internal consistency reliability was confirmed through Cronbach's Alpha, Composite Reliability, and rho_A values exceeding the recommended threshold. Convergent validity was supported by Average Variance Extracted (AVE) values above 0.50 for all constructs.

Discriminant validity was verified using both the Fornell-Larcker Criterion and the Heterotrait-Monotrait Ratio (HTMT), which confirmed that the constructs are empirically distinct from one another. In addition, the Variance Inflation Factor (VIF) values remained within acceptable limits, indicating the absence of multicollinearity concerns.

Overall, the results demonstrate that the measurement model possesses satisfactory reliability and validity. Having established the adequacy of the measurement model, the analysis proceeds to the evaluation of the structural model and hypothesis testing.

4.5 Structural Model Assessment

Following the establishment of a reliable and valid measurement model, the structural model was evaluated to examine the hypothesized relationships among the study constructs and assess the explanatory power of the proposed framework. In PLS-SEM, structural model assessment focuses on the magnitude, direction, and significance of the relationships among latent variables (Hair et al., 2022).

The structural model was evaluated using path coefficients, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and bootstrapping procedures. In addition, mediation and moderation analyses were conducted to examine the indirect effects of Screen Use Intensity and Screen Addiction, as well as the moderating role of Asymmetric Information.

The findings presented in this section provide empirical evidence regarding the relationships among Digital Access, Asymmetric Information, Screen Use Intensity, Screen Addiction, Impact on Productivity, and Mental Hygiene.

4.5.1 Collinearity Assessment

Prior to hypothesis testing, collinearity diagnostics were conducted to ensure that the predictor constructs did not exhibit excessive correlation. In PLS-SEM, collinearity is assessed using the Variance Inflation Factor (VIF). According to Hair et al. (2022), VIF values below 5.0 indicate that collinearity is not a serious concern.

Table 4.13: Inner VIF Values

Structural Relationship	VIF
AS → SA	1.349
AS → SUI	1.349
AS × DA → SA	1.016
AS × DA → SUI	1.016
DA → SA	1.331
DA → SUI	1.331
SA → IP	1.557
SA → MH	1.557
SUI → IP	1.557
SUI → MH	1.557

Source: Author's computation using SmartPLS 4.

The VIF values range from 1.016 to 1.557, which are substantially below the recommended threshold of 5.0. These results indicate the absence of problematic collinearity among the predictor constructs. Consequently, the estimated path coefficients can be interpreted with confidence, and the structural model is suitable for hypothesis testing. "'latex

4.5.2 Structural Model Diagram

Figure 4.2 presents the final structural model estimated using SmartPLS 4. The model illustrates the relationships among Digital Access (DA), Asymmetric Information (AS), Screen Use Intensity (SUI), Screen Addiction (SA), Impact on Productivity (IP), and Mental Hygiene (MH). In addition, the model incorporates the interaction term (AS × DA) to examine the moderating role of Asymmetric Information in the relationship between Digital Access and behavioural outcomes.

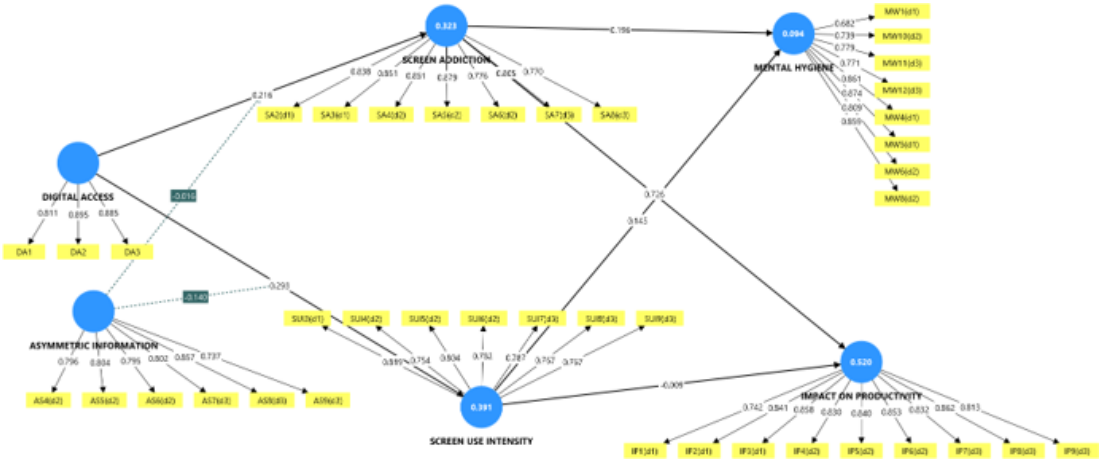


Figure 4.2: Structural Model Results

Source: Author's computation using SmartPLS 4.

The model explains 39.1 percent of the variance in Screen Use Intensity ($R^2 = 0.391$), 32.3 percent of the variance in Screen Addiction ($R^2 = 0.323$), 52.0 percent of the variance in Impact on Productivity ($R^2 = 0.520$). The structural model provides a graphical representation of the hypothesized relationships among the study constructs. The values displayed on the measurement indicators represent the outer loadings, while the values associated with the endogenous constructs indicate the coefficient of determination (R^2). The path coefficients shown along the structural paths represent the estimated relationships among the latent variables.

4.5.3 Path Coefficient Analysis

Following the assessment of collinearity, the structural relationships proposed in the conceptual framework were examined through path coefficient analysis. Path coefficients (β) indicate the direction and magnitude of relationships among latent constructs, while statistical significance was evaluated through the bootstrapping procedure in SmartPLS 4.

Table 4.14: Path Coefficients and Bootstrapping Results

Structural Path	O	M	STDEV	T Statistics	P Values
AS → SA	0.426	0.426	0.071	6.005	0.000
AS → SUI	0.382	0.385	0.080	4.754	0.000
AS × DA → SA	-0.016	-0.015	0.046	0.338	0.735
AS × DA → SUI	-0.140	-0.139	0.047	3.003	0.003
DA → SA	0.216	0.221	0.076	2.860	0.004
DA → SUI	0.293	0.296	0.078	3.748	0.000
SA → IP	0.726	0.728	0.048	15.233	0.000
SA → MH	0.196	0.204	0.099	1.973	0.049
SUI → IP	-0.009	-0.007	0.063	0.145	0.885
SUI → MH	0.145	0.152	0.107	1.351	0.177

Source: Author's computation using SmartPLS 4.

Note: O = Original Sample; M = Sample Mean; STDEV = Standard Deviation.

The results presented in Table 4.14 indicate that Digital Access has a positive and statistically significant effect on Screen Use Intensity ($\beta = 0.293$, $p < 0.001$) and Screen Addiction ($\beta = 0.216$, $p = 0.004$). This suggests that greater access to digital devices, internet connectivity, and online platforms is associated with higher levels of digital engagement and addictive usage patterns.

Asymmetric Information also exhibits positive and statistically significant effects on Screen Use Intensity ($\beta = 0.382$, $p < 0.001$) and Screen Addiction ($\beta = 0.426$, $p < 0.001$). The magnitude of these coefficients is higher than the corresponding effects of Digital Access, indicating that informational imbalance between platforms and users plays an important role in shaping digital behaviour.

Among the outcome relationships, Screen Addiction has a strong positive effect on Impact on Productivity ($\beta = 0.726$, $p < 0.001$), representing the largest coefficient in the model. Screen Addiction also shows a positive and statistically significant effect on Mental Hygiene ($\beta = 0.196$, $p = 0.049$). These findings indicate that addictive digital behaviour is closely associated with productivity-related difficulties and adverse psychological outcomes.

In contrast, Screen Use Intensity does not significantly influence either Impact on Productivity ($\beta = -0.009$, $p = 0.885$) or Mental Hygiene ($\beta = 0.145$, $p = 0.177$). This suggests that the extent of screen use alone is insufficient to explain adverse outcomes unless it develops into addictive or compulsive usage behaviour.

With respect to moderation, the interaction between Asymmetric Information and Digital Access does not significantly influence Screen Addiction ($\beta = -0.016$, $p = 0.735$). However, the interaction effect on Screen Use Intensity is negative and statistically significant ($\beta = -0.140$, $p = 0.003$). This indicates that the positive effect of Digital Access on Screen Use Intensity weakens at higher levels of Asymmetric Information.

Overall, the findings suggest that Digital Access and Asymmetric Information significantly influence digital engagement behaviours, while Screen Addiction is the principal predictor of Impact on Productivity and Mental Hygiene. The results further indicate that Screen Use Intensity alone does not generate significant adverse outcomes, highlighting the importance of distinguishing between intensive use and addictive use in the analysis of digital behaviour.

4.5.4 Hypothesis Testing

The significance of the proposed hypotheses was evaluated using the bootstrapping procedure in SmartPLS 4. Hypotheses were considered supported when the corresponding path coefficient was statistically significant at the 5 percent significance level ($p < 0.05$). The results of hypothesis testing are presented in Table 4.15.

Table 4.15: Hypothesis Testing Results

Hypothesis	Relationship	β	t-value	p-value	Decision
H1	DA → SUI	0.293	3.748	0.000	Supported
H2	DA → SA	0.216	2.860	0.004	Supported
H3	SUI → IP	-0.009	0.145	0.885	Not Supported
H4	SA → IP	0.726	15.233	0.000	Supported
H5	SUI → MH	0.145	1.351	0.177	Not Supported
H6	SA → MH	0.196	1.973	0.049	Supported
H7	AS → SUI	0.382	4.754	0.000	Supported
H8	AS → SA	0.426	6.005	0.000	Supported
H9	AS × DA → SUI	-0.140	3.003	0.003	Supported
H10	AS × DA → SA	-0.016	0.338	0.735	Not Supported

Source: Author's computation using SmartPLS 4.

The hypothesis testing results indicate that seven out of the ten proposed hypotheses are supported. Digital Access significantly influences both Screen Use Intensity and Screen Addiction, supporting H1 and H2. However, Screen Use Intensity does not significantly affect either Impact on Productivity or Mental Hygiene, leading to the rejection of H3 and H5.

Screen Addiction exhibits significant positive effects on both Impact on Productivity and Mental Hygiene, supporting H4 and H6. These findings suggest that adverse

behavioural outcomes are primarily associated with addictive digital behaviour rather than screen exposure alone.

The results further show that Asymmetric Information significantly influences Screen Use Intensity and Screen Addiction, providing support for H7 and H8. With respect to moderation, the interaction effect of Asymmetric Information and Digital Access on Screen Use Intensity is significant, supporting H9. In contrast, the interaction effect on Screen Addiction is not significant, resulting in the rejection of H10.

Overall, the findings highlight Screen Addiction as the principal mechanism linking digital engagement with productivity-related and psychological outcomes, while Asymmetric Information emerges as an important determinant of behavioural engagement within digital environments.

4.6 Explanatory Power and Predictive Relevance

Following hypothesis testing, the explanatory and predictive capabilities of the structural model were evaluated using the coefficient of determination (R^2) and Stone-Geisser's predictive relevance statistic (Q^2). These measures assess the extent to which the model explains and predicts the endogenous constructs included in the study.

4.6.1 Coefficient of Determination (R^2)

The coefficient of determination (R^2) indicates the proportion of variance in an endogenous construct explained by its predictor variables. According to Hair et al. (2022), R^2 values of 0.75, 0.50, and 0.25 may be interpreted as substantial, moderate, and weak explanatory power, respectively.

Table 4.16: Coefficient of Determination (R^2)

Endogenous Construct	R^2	**Adjusted** R^2
Impact on Productivity	0.520	0.514
Mental Hygiene	0.094	0.083
Screen Addiction	0.323	0.311
Screen Use Intensity	0.391	0.381

Source: Author's computation using SmartPLS 4.

The results indicate that the model explains 52.0 percent of the variance in Impact on Productivity ($R^2 = 0.520$), representing the highest explanatory power among the endogenous constructs. This suggests that Screen Addiction and Screen Use Intensity jointly provide substantial explanatory power for productivity-related outcomes.

The model explains 39.1 percent of the variance in Screen Use Intensity and 32.3 percent of the variance in Screen Addiction, indicating moderate explanatory power. These findings suggest that Digital Access, Asymmetric Information, and their interaction contribute meaningfully to behavioural engagement outcomes.

In contrast, the explanatory power for Mental Hygiene is relatively low ($R^2 = 0.094$), indicating that the variables included in the model account for only 9.4 percent

of its variance. This suggests that mental well-being is influenced by additional factors beyond those incorporated in the present framework.

Overall, the R^2 results demonstrate moderate explanatory capability for behavioural and productivity-related outcomes, with the strongest explanatory power observed for Impact on Productivity.

4.6.2 Effect Size (f^2)

While the coefficient of determination (R^2) assesses the overall explanatory power of the model, effect size (f^2) evaluates the individual contribution of each predictor construct to an endogenous construct. The f^2 statistic measures the change in R^2 when a specific exogenous construct is omitted from the model. Following Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively.

Table 4.17: Effect Size (f^2)

Relationship	f^2
Asymmetric Information → Screen Addiction	0.198
Asymmetric Information → Screen Use Intensity	0.178
Asymmetric Information × Digital Access → Screen Addiction	0.001
Asymmetric Information × Digital Access → Screen Use Intensity	0.046
Digital Access → Screen Addiction	0.052
Digital Access → Screen Use Intensity	0.106
Screen Addiction → Impact on Productivity	0.705
Screen Addiction → Mental Hygiene	0.027
Screen Use Intensity → Impact on Productivity	0.000
Screen Use Intensity → Mental Hygiene	0.015

Source: Author's computation using SmartPLS 4.

The effect size analysis reveals considerable variation in the contribution of individual predictors across the endogenous constructs. The strongest effect is observed for the relationship between Screen Addiction and Impact on Productivity ($f^2 = 0.705$), which substantially exceeds the threshold for a large effect. This finding indicates that Screen Addiction is the dominant predictor of productivity-related outcomes within the model and reinforces its role as the principal behavioural mechanism linking digital engagement to economic consequences.

Asymmetric Information exhibits medium effect sizes on both Screen Addiction ($f^2 = 0.198$) and Screen Use Intensity ($f^2 = 0.178$), highlighting the importance of informational imbalances in shaping user behaviour. These results suggest that platform-level informational advantages contribute meaningfully to both digital engagement and the development of addictive usage patterns.

Digital Access demonstrates small effects on Screen Addiction ($f^2 = 0.052$) and Screen Use Intensity ($f^2 = 0.106$), indicating that although access facilitates digital

participation, its contribution is less substantial than that of Asymmetric Information. The interaction effect between Asymmetric Information and Digital Access exhibits a negligible effect on Screen Addiction ($f^2 = 0.001$) and a small effect on Screen Use Intensity ($f^2 = 0.046$).

Finally, Screen Use Intensity displays negligible effects on both Impact on Productivity ($f^2 = 0.000$) and Mental Hygiene ($f^2 = 0.015$). These findings are consistent with the hypothesis testing results and suggest that screen exposure alone contributes little to adverse outcomes unless it develops into addictive behaviour.

Overall, the f^2 analysis confirms that Screen Addiction is the most influential predictor in the model, while Asymmetric Information represents an important antecedent of behavioural engagement within digital environments.

4.6.3 Predictive Relevance (Q^2)

Beyond explanatory power, the predictive capability of the structural model was assessed using Stone-Geisser's Q^2 statistic obtained through the blindfolding procedure. Whereas R^2 evaluates the explanatory power of the model, Q^2 assesses its predictive relevance. According to Hair et al. (2022), Q^2 values greater than zero indicate that the model possesses predictive relevance for a given endogenous construct.

Table 4.18: Predictive Relevance (Q^2)

Endogenous Construct	Q^2	**RMSE**	**MAE**
Screen Addiction	0.297	0.847	0.668
Screen Use Intensity	0.353	0.813	0.636
Impact on Productivity	0.140	0.939	0.740
Mental Hygiene	0.110	0.953	0.714

Source: Author's computation using SmartPLS 4.

The results indicate that all endogenous constructs exhibit positive Q^2 values, thereby confirming the predictive relevance of the structural model. Among the endogenous variables, Screen Use Intensity records the highest predictive relevance ($Q^2 = 0.353$), followed by Screen Addiction ($Q^2 = 0.297$). These findings suggest that the model demonstrates relatively strong predictive capability for behavioural outcomes associated with digital engagement.

The predictive relevance for Impact on Productivity ($Q^2 = 0.140$) and Mental Hygiene ($Q^2 = 0.110$) is comparatively lower but remains above the recommended threshold of zero. This indicates that the model retains meaningful predictive capability for both outcome constructs, although additional determinants beyond those incorporated in the present framework are likely to influence productivity and psychological well-being.

The RMSE and MAE values provide supplementary information regarding prediction accuracy. The relatively lower prediction errors observed for Screen Use Intensity and Screen Addiction are consistent with their higher Q^2 values and further support the model's stronger predictive performance for behavioural constructs.

Overall, the positive Q^2 values across all endogenous constructs confirm that the proposed model possesses satisfactory predictive relevance. The findings suggest that the framework is capable of predicting both behavioural and outcome variables within the sample and therefore provides a useful basis for understanding the relationships among Digital Access, Asymmetric Information, Screen Use Intensity, Screen Addiction, Impact on Productivity, and Mental Hygiene.

4.6.4 Summary of Explanatory Power and Predictive Relevance

The assessment of explanatory power and predictive relevance provides further evidence regarding the adequacy of the proposed structural model. The R^2 results indicate moderate explanatory power for the key behavioural constructs and productivity-related outcomes, with the highest explanatory capability observed for Impact on Productivity ($R^2 = 0.520$), followed by Screen Use Intensity ($R^2 = 0.391$) and Screen Addiction ($R^2 = 0.323$). Mental Hygiene exhibited comparatively lower explanatory power ($R^2 = 0.094$), suggesting that additional factors beyond those included in the present model may influence psychological well-being.

The f^2 analysis revealed substantial variation in the contribution of individual predictors across endogenous constructs. The strongest effect was observed for the relationship between Screen Addiction and Impact on Productivity ($f^2 = 0.705$), while Asymmetric Information demonstrated meaningful effects on both Screen Addiction and Screen Use Intensity. In contrast, Screen Use Intensity exhibited negligible effects on Impact on Productivity and Mental Hygiene.

The predictive relevance assessment further confirmed the robustness of the model. All endogenous constructs recorded positive Q^2 values, thereby satisfying the criterion for predictive relevance. The strongest predictive capability was observed for Screen Use Intensity ($Q^2 = 0.353$) and Screen Addiction ($Q^2 = 0.297$), indicating satisfactory predictive performance for the behavioural constructs included in the model.

Overall, the R^2, f^2, and Q^2 results support the explanatory and predictive adequacy of the proposed framework. Among the relationships examined, Screen Addiction emerged as the most influential construct, particularly in explaining variations in Impact on Productivity. These findings provide a strong empirical foundation for the subsequent evaluation of model fit, mediation effects, and moderation effects.

4.7 Model Fit Assessment

Following the assessment of the structural relationships, explanatory power, and predictive relevance, overall model fit was evaluated to provide additional evidence regarding the adequacy of the proposed model. Although PLS-SEM primarily emphasises prediction and explanation, Hair et al. (2022) recommended reporting model fit indices as supplementary indicators of model quality.

Table 4.19: Model Fit Indices

Fit Measure	Saturated Model	Estimated Model
SRMR	0.070	0.094
d_{ULS}	4.027	7.214
d_G	1.674	1.730
Chi-square	1501.644	1539.365
NFI	0.743	0.736

Source: Author's computation using SmartPLS 4.

The SRMR values obtained for the saturated model (0.070) and estimated model (0.094) indicate an acceptable level of model fit. Hu and Bentler (1999) suggested that SRMR values below 0.10 reflect satisfactory correspondence between the observed and model-implied correlation matrices. The obtained values therefore support the adequacy of the proposed model.

The NFI values of 0.743 and 0.736 indicate a reasonable improvement over the null model. Hair et al. (2022) noted that NFI values in PLS-SEM should be interpreted alongside measures of reliability, validity, explanatory power, and predictive relevance rather than as standalone indicators of model adequacy.

The discrepancy measures (d_{ULS} and d_G) do not indicate substantial divergence between the empirical and model-implied correlation matrices. Similarly, the Chi-square statistics are reported for completeness but are interpreted cautiously because of their sensitivity to sample size and model complexity.

Overall, the model fit assessment provides additional support for the adequacy of the proposed framework. Together with the satisfactory reliability, convergent validity, discriminant validity, explanatory power, and predictive relevance established in the preceding sections, the findings indicate that the model is appropriately specified for examining the relationships among Digital Access, Asymmetric Information, Screen Use Intensity, Screen Addiction, Impact on Productivity, and Mental Hygiene.

4.8 Mediation Analysis

Mediation analysis was conducted to examine whether Screen Use Intensity (SUI) and Screen Addiction (SA) function as intervening mechanisms linking Digital Access (DA) and Asymmetric Information (AS) with Impact on Productivity (IP) and Mental Hygiene (MH). The significance of indirect effects was assessed using the bootstrapping procedure in SmartPLS 4. Following Hair et al. (2022), mediation is established when the indirect effect is statistically significant.

4.8.1 Specific Indirect Effects

Table 4.20 presents the bootstrapped indirect effects.

Table 4.20: Specific Indirect Effects

Indirect Relationship	O	M	STDEV	t-value	p-value
AS×DA → SUI → IP	-0.000	-0.000	0.010	0.029	0.977
AS×DA → SA → IP	-0.010	-0.009	0.034	0.285	0.776
AS×DA → SUI → MH	-0.011	-0.010	0.015	0.721	0.471
AS×DA → SA → MH	-0.002	-0.002	0.009	0.231	0.817
AS → SUI → IP	0.001	0.002	0.028	0.029	0.977
AS → SA → IP	0.313	0.315	0.056	5.633	0.000
AS → SUI → MH	0.030	0.033	0.043	0.697	0.486
AS → SA → MH	0.066	0.068	0.051	1.285	0.199
DA → SUI → IP	0.001	0.002	0.021	0.029	0.977
DA → SA → IP	0.157	0.160	0.057	2.728	0.006
DA → SUI → MH	0.023	0.022	0.032	0.723	0.470
DA → SA → MH	0.033	0.032	0.026	1.241	0.215

Source: Author's computation using SmartPLS 4.

The mediation results indicate that only two indirect effects are statistically significant. Asymmetric Information exerts a significant indirect effect on Impact on Productivity through Screen Addiction ($\beta = 0.313$, $p < 0.001$), while Digital Access also influences Impact on Productivity indirectly through Screen Addiction ($\beta = 0.157$, $p = 0.006$).

In contrast, none of the indirect pathways operating through Screen Use Intensity were significant. Similarly, all indirect effects leading to Mental Hygiene failed to achieve statistical significance. The moderated mediation pathways involving the interaction term between Asymmetric Information and Digital Access were likewise insignificant.

These findings suggest that Screen Addiction serves as the primary behavioural mechanism through which Digital Access and Asymmetric Information affect productivity outcomes. The absence of significant mediation through Screen Use Intensity indicates that screen exposure alone is insufficient to explain productivity-related consequences. Rather, adverse outcomes emerge when digital engagement develops into addictive behavioural patterns.

Overall, the mediation analysis highlights the central role of Screen Addiction within the proposed framework and provides further evidence that behavioural dependency constitutes the key pathway linking the attention economy to productivity loss.

4.9 Mediation Analysis

While the structural model provides evidence regarding the direct relationships among the study variables, mediation analysis offers deeper insight into the behavioural mechanisms through which these relationships operate. Mediation analysis was conducted to examine whether Screen Use Intensity (SUI) and Screen Addiction (SA) function as intervening variables linking Digital Access (DA) and Asymmetric Information (AS) with Impact on Productivity (IP) and Mental Hygiene (MH). The significance of indi-

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rect effects was assessed using the bootstrapping procedure in SmartPLS 4. Following Hair et al. (2022), mediation is established when the indirect effect is statistically significant.

The mediation analysis is particularly relevant because it helps identify whether adverse outcomes arise from digital engagement itself or from the development of behavioural dependency associated with digital platform use.

4.9.1 Indirect Effects

Table 4.21 presents the specific indirect effects obtained through bootstrapping.

Table 4.21: Specific Indirect Effects

Indirect Relationship	O	M	STDEV	t-value	p-value
AS × DA → SUI → IP	-0.000	-0.000	0.010	0.029	0.977
AS × DA → SA → IP	-0.010	-0.009	0.034	0.285	0.776
AS × DA → SUI → MH	-0.011	-0.010	0.015	0.721	0.471
AS × DA → SA → MH	-0.002	-0.002	0.009	0.231	0.817
AS → SUI → IP	0.001	0.002	0.028	0.029	0.977
AS → SA → IP	0.313	0.315	0.056	5.633	0.000
AS → SUI → MH	0.030	0.033	0.043	0.697	0.486
DA → SUI → IP	0.001	0.002	0.021	0.029	0.977
AS → SA → MH	0.066	0.068	0.051	1.285	0.199
DA → SA → IP	0.157	0.160	0.057	2.728	0.006
DA → SUI → MH	0.023	0.022	0.032	0.723	0.470
DA → SA → MH	0.033	0.032	0.026	1.241	0.215

Source: Author's computation using SmartPLS 4.

The results indicate that only two indirect pathways are statistically significant. Specifically, Asymmetric Information exerts a significant indirect effect on Impact on Productivity through Screen Addiction ($\beta = 0.313$, $p < 0.001$). Similarly, Digital Access demonstrates a significant indirect effect on Impact on Productivity through Screen Addiction ($\beta = 0.157$, $p = 0.006$).

In contrast, none of the indirect effects operating through Screen Use Intensity achieved statistical significance. Likewise, all indirect effects leading to Mental Hygiene were found to be statistically insignificant. The moderated mediation pathways involving the interaction between Asymmetric Information and Digital Access also failed to attain statistical significance.

These findings indicate that the influence of Digital Access and Asymmetric Information on productivity outcomes is transmitted primarily through Screen Addiction rather than through Screen Use Intensity.

4.9.2 Mediation through Screen Use Intensity

The mediation analysis provides no evidence that Screen Use Intensity functions as a significant mediator within the proposed framework. Although Digital Access and Asymmetric Information significantly influence Screen Use Intensity, the indirect effects transmitted through this construct were not statistically significant.

The indirect effects of Digital Access and Asymmetric Information on Impact on Productivity through Screen Use Intensity were both insignificant ($\beta = 0.001$, $p =$

0.977). Similarly, the indirect effects on Mental Hygiene through Screen Use Intensity were not statistically significant for either Digital Access ($\beta = 0.023$, $p = 0.470$) or Asymmetric Information ($\beta = 0.030$, $p = 0.486$).

These findings suggest that increased screen exposure alone does not constitute a meaningful mechanism through which digital engagement influences productivity or mental well-being. Consequently, Screen Use Intensity does not mediate any of the relationships examined in the present study.

4.9.3 Mediation through Screen Addiction

A different pattern emerged for Screen Addiction. The results indicate that Screen Addiction serves as a significant mediator linking both Digital Access and Asymmetric Information with Impact on Productivity.

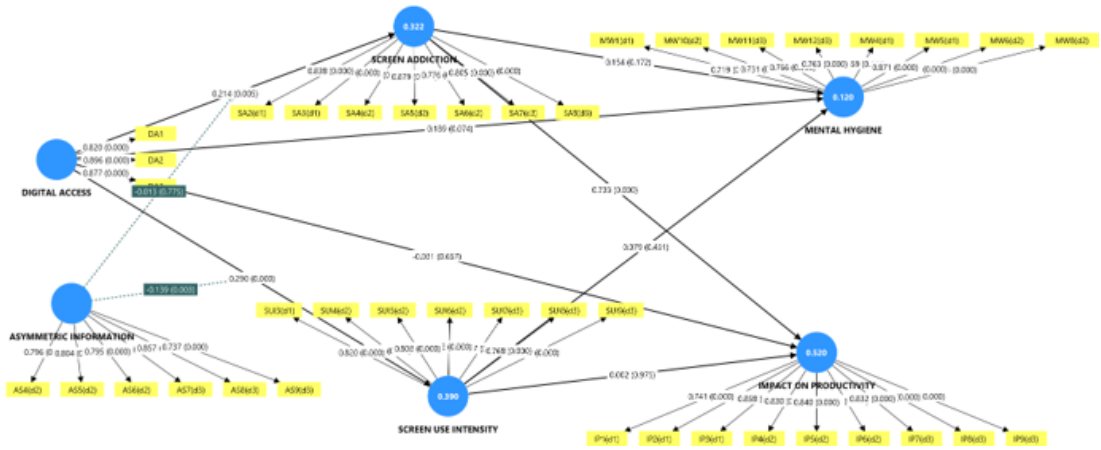


Figure 4.3: Final Mediation Model Showing Direct and Indirect Effects

As shown in Figure 4.3, significant indirect effects were observed primarily through Screen Addiction, whereas the indirect pathways operating through Screen Use Intensity remained statistically insignificant.

The indirect effect of Asymmetric Information on Impact on Productivity through Screen Addiction was positive and statistically significant ($\beta = 0.313$, $p < 0.001$). Similarly, Digital Access exerted a significant indirect effect on Impact on Productivity through Screen Addiction ($\beta = 0.157$, $p = 0.006$).

In contrast, no significant indirect effects were observed through Screen Addiction for Mental Hygiene. The indirect effects of Digital Access ($\beta = 0.033$, $p = 0.215$) and Asymmetric Information ($\beta = 0.066$, $p = 0.199$) on Mental Hygiene through Screen Addiction were statistically insignificant.

Overall, the results identify Screen Addiction as a key behavioural pathway linking digital environments to productivity-related outcomes. The findings suggest that the adverse consequences associated with digital technologies emerge not simply because individuals use them extensively, but because such environments may foster dependency-oriented patterns of engagement that interfere with productive activity.

4.9.4 Summary of Mediation Analysis

Table 4.22 summarises the mediation results.

Table 4.22: Summary of Mediation Analysis

Relationship	Mediator	β	p-value	Mediation Type
DA → IP	SUI	0.001	0.977	No Mediation
AS → IP	SUI	0.001	0.977	No Mediation
DA → MH	SUI	0.023	0.470	No Mediation
AS → MH	SUI	0.030	0.486	No Mediation
DA → IP	SA	0.157	0.006	Complementary Partial Mediation
AS → IP	SA	0.313	0.000	Complementary Partial Mediation
DA → MH	SA	0.033	0.215	No Mediation
AS → MH	SA	0.066	0.199	No Mediation

Source: Author's computation using SmartPLS 4.

Source: Author's computation using SmartPLS 4.

The mediation analysis revealed a clear distinction between the roles of Screen Use Intensity and Screen Addiction. Screen Use Intensity did not mediate any of the relationships examined in the study, as none of the indirect effects operating through this construct were statistically significant.

In contrast, Screen Addiction emerged as a significant mediator between both Digital Access and Asymmetric Information and Impact on Productivity. Significant indirect effects were observed for the pathways Digital Access → Screen Addiction → Impact on Productivity and Asymmetric Information → Screen Addiction → Impact on Productivity. However, no significant indirect effects were identified for Mental Hygiene.

Overall, the findings indicate that the behavioural consequences of digital engagement are transmitted primarily through addictive patterns of digital engagement rather than through screen usage intensity. The results therefore identify Screen Addiction as the principal behavioural mechanism linking digital market conditions to productivity-related outcomes.

4.10 Moderation Analysis

Moderation analysis was conducted to examine whether Asymmetric Information (AS) changes the strength or direction of the relationship between Digital Access (DA) and digital behavioural outcomes. Specifically, the analysis assessed whether the effect of Digital Access on Screen Use Intensity (SUI) and Screen Addiction (SA) varies at different levels of Asymmetric Information.

The moderating effect was tested by creating an interaction term between Asymmetric Information and Digital Access (AS × DA) in SmartPLS 4. The statistical significance of the interaction effects was evaluated using the bootstrapping procedure. The results are presented in Table 4.23.

Table 4.23: Moderation Analysis Results

Relationship	β	t-value	p-value	Decision
AS × DA → Screen Use Intensity	-0.139	2.956	0.003	Supported
AS × DA → Screen Addiction	-0.013	0.286	0.775	Not Supported

Source: Author's computation using SmartPLS 4.

The results indicate that Asymmetric Information significantly moderates the relationship between Digital Access and Screen Use Intensity ($\beta = -0.139$, $p = 0.003$). The negative coefficient suggests that the positive effect of Digital Access on Screen Use Intensity weakens as Asymmetric Information

increases. This indicates that when users experience higher informational asymmetry, differences in digital access become less influential in explaining variations in screen use intensity.

In contrast, the interaction effect of Asymmetric Information and Digital Access on Screen Addiction is statistically insignificant ($\beta = -0.013$, $p = 0.775$). This finding indicates that Asymmetric Information does not significantly alter the relationship between Digital Access and Screen Addiction.

Overall, the moderation analysis provides partial support for the moderating role of Asymmetric Information. While Asymmetric Information significantly conditions the relationship between Digital Access and Screen Use Intensity, it does not significantly moderate the relationship between Digital Access and Screen Addiction. Therefore, the moderating influence of Asymmetric Information appears to be limited to screen use behaviour rather than addictive digital behaviour.

4.10.1 Moderating Role of Asymmetric Information

The moderation analysis examined whether Asymmetric Information alters the relationship between Digital Access and the behavioural outcomes included in the model. The results indicate that the moderating effect of Asymmetric Information is selective. While the interaction term significantly influences Screen Use Intensity, no significant moderation effect was observed for Screen Addiction.

These findings suggest that informational asymmetry conditions the extent to which Digital Access translates into digital engagement behaviour. However, the development of addictive behaviour appears to be influenced primarily by the direct effects of Digital Access and Asymmetric Information rather than by their interaction.

4.10.2 Interaction Effect of Asymmetric Information and Digital Access on Screen Use Intensity

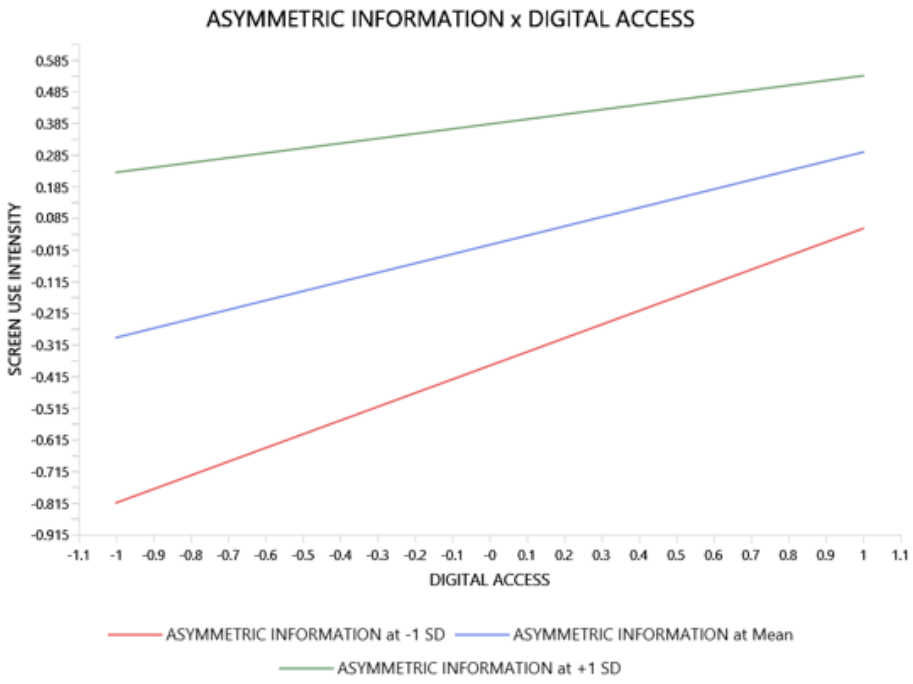


Figure 4.4: Interaction Plot: Asymmetric Information × Digital Access → Screen Use Intensity

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Figure 4.4 presents the interaction effect at low (-1 SD), mean, and high ($+1$ SD) levels of Asymmetric Information. The interaction term was negative and statistically significant ($\beta = -0.139$, $p = 0.003$), indicating that Asymmetric Information moderates the relationship between Digital Access and Screen Use Intensity.

The interaction plot shows that Digital Access positively influences Screen Use Intensity across all levels of Asymmetric Information. However, the slope becomes flatter as Asymmetric Information increases, indicating that the positive effect of Digital Access weakens at higher levels of informational asymmetry.

This finding suggests that when informational asymmetry is relatively low, differences in Digital Access explain a larger proportion of variation in screen engagement. In contrast, under conditions of high informational asymmetry, engagement becomes less dependent on access and more influenced by platform-driven mechanisms such as algorithmic recommendations, behavioural tracking, and personalised content delivery.

The result implies that informational advantages possessed by digital platforms partially reduce the importance of access in shaping engagement behaviour. Consequently, user attention appears to be influenced not only by the availability of digital technologies but also by the informational power embedded within platform ecosystems.

Overall, the moderation results indicate that Asymmetric Information functions as a conditioning factor in the relationship between Digital Access and Screen Use Intensity. However, no comparable moderating effect was observed for Screen Addiction, suggesting that informational asymmetry primarily affects engagement intensity rather than the development of addictive digital behaviour.

4.10.3 Interaction Effect of Asymmetric Information and Digital Access on Screen Addiction

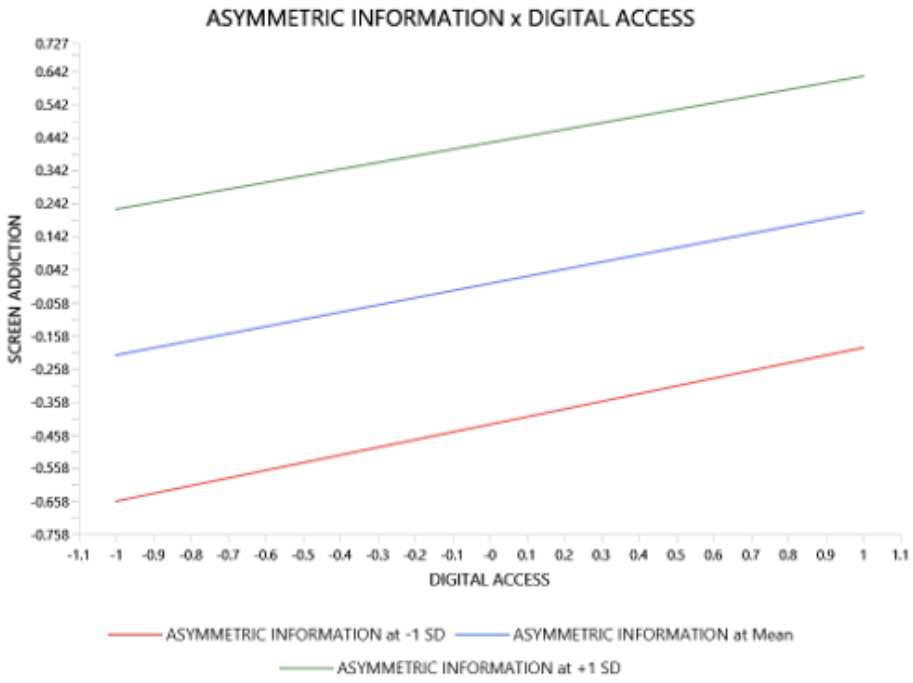


Figure 4.5: Interaction Plot: Asymmetric Information $\times$ Digital Access $\rightarrow$ Screen Addiction

The interaction effect between Asymmetric Information and Digital Access on Screen Addiction was not statistically significant ($\beta = -0.013$, $p = 0.775$). Consequently, no evidence was found to support

the moderating role of Asymmetric Information in the relationship between Digital Access and Screen Addiction.

As illustrated in Figure 4.5, the slopes corresponding to low (-1 SD), mean, and high ($+1$ SD) levels of Asymmetric Information are largely parallel. Although minor differences are visible across the three lines, these variations are not statistically significant and therefore do not indicate a meaningful interaction effect.

The result suggests that the influence of Digital Access on Screen Addiction remains relatively stable across different levels of informational asymmetry. In other words, greater access to digital technologies increases the likelihood of addictive digital behaviour irrespective of whether users operate in environments characterised by low or high informational asymmetry.

This finding implies that Screen Addiction is primarily explained by the direct effects of Digital Access and Asymmetric Information rather than by their interaction. Accordingly, the behavioural mechanisms underlying addictive digital engagement appear to be relatively independent of variations in informational asymmetry.

4.10.4 Summary of Moderation Results

The moderation analysis provides partial support for the proposed moderating role of Asymmetric Information. A significant interaction effect was observed for the relationship between Digital Access and Screen Use Intensity, indicating that the effect of Digital Access on engagement intensity varies across different levels of informational asymmetry.

However, no significant moderation effect was observed for Screen Addiction. The relationship between Digital Access and Screen Addiction remained stable irrespective of the level of Asymmetric Information.

Overall, the findings suggest that informational asymmetry influences engagement intensity but does not significantly alter the process through which Digital Access contributes to addictive digital behaviour. These results highlight the selective nature of the moderating role of Asymmetric Information within the proposed framework.

4.11 Conclusion

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This chapter presented the empirical analysis of the proposed research model using Exploratory Factor Analysis (EFA) and Partial Least Squares Structural Equation Modelling (PLS-SEM). The analysis examined the relationships among Digital Access, Asymmetric Information, Screen Use Intensity, Screen Addiction, Impact on Productivity, and Mental Hygiene.

The respondent profile indicated that the sample consisted predominantly of digitally active individuals with substantial exposure to digital technologies and online platforms. The EFA results confirmed the suitability of the measurement instrument and supported the six-factor structure proposed in the conceptual framework. Subsequent measurement model assessment established satisfactory reliability, convergent validity, discriminant validity, and the absence of multicollinearity concerns, confirming the adequacy of the measurement model for structural analysis.

The structural model results demonstrated that both Digital Access and Asymmetric Information significantly influence Screen Use Intensity and Screen Addiction. Among the antecedent variables, Asymmetric Information exerted a comparatively stronger influence on behavioural outcomes, highlighting the importance of informational advantages embedded within digital platforms. The findings further revealed that Screen Addiction significantly affects Impact on Productivity, whereas Screen Use Intensity does not exert a significant influence on either productivity or mental hygiene outcomes.

The mediation analysis identified Screen Addiction as the primary behavioural mechanism linking Digital Access and Asymmetric Information to productivity-related outcomes. In contrast, Screen Use Intensity did not function as a significant mediator. These findings suggest that the adverse consequences associated with digital engagement arise primarily through addictive patterns of use rather than through screen exposure alone.

The moderation analysis provided partial support for the moderating role of Asymmetric Informa-

tion. A significant interaction effect was observed for Screen Use Intensity, indicating that the influence of Digital Access on engagement intensity varies across levels of informational asymmetry. However, no significant moderation effect was found for Screen Addiction.

The explanatory and predictive assessments further confirmed the adequacy of the proposed framework. The model demonstrated moderate explanatory power for the principal endogenous constructs and satisfactory predictive relevance. Collectively, these results indicate that the proposed model provides a meaningful explanation of the behavioural pathways through which digital environments influence user outcomes.

Overall, the empirical findings highlight the central role of Screen Addiction within the proposed framework. The results suggest that Digital Access and Asymmetric Information contribute to adverse outcomes primarily when digital engagement develops into behavioural dependency. These findings provide the empirical foundation for Chapter 5, which discusses the results in relation to the theoretical framework, existing literature, policy implications, and the broader economic implications of the attention economy.

Chapter 5

DISCUSSION, CONCLUSION AND IMPLICATIONS

5.1 Introduction

The increasing centrality of digital platforms in economic and social life has intensified scholarly interest in the allocation and monetisation of human attention. Simon (1971) argued that in an information-rich environment, the abundance of information creates a scarcity of attention, thereby making attention a valuable economic resource. Building on this idea, Goldhaber (1997) proposed that attention functions as a form of currency in digital environments, while Davenport and Beck (2001) emphasized its growing importance as a strategic resource in modern economies. Consequently, digital platforms increasingly compete not only for users but also for their time, engagement, and behavioural participation.

The expansion of data-driven platform ecosystems has further transformed the dynamics of digital markets. Wu (2016) observed that contemporary digital business models are designed to capture and retain user attention, whereas Zuboff (2019) highlighted how behavioural data and predictive analytics enable platforms to influence user behaviour on an unprecedented scale. Although these developments have generated significant benefits in terms of information access, connectivity, communication, and economic opportunities, they have also raised concerns regarding excessive engagement, behavioural dependency, productivity loss, and psychological well-being.

The present study examined the behavioural pathways through which Digital Access and Asymmetric Information influence digital engagement outcomes. Drawing upon Attention Economy Theory, Information Asymmetry Theory, and Behavioural Economics, the study developed and empirically tested a framework linking Digital Access and Asymmetric Information with Screen Use Intensity, Screen Addiction, Impact on Productivity, and Mental Hygiene. The study further investigated the mediating roles of Screen Use Intensity and Screen Addiction and examined whether Asymmetric Information moderates the relationship between Digital Access and digital behavioural outcomes.

The empirical analysis presented in Chapter 4 established that both Digital Access and Asymmetric Information significantly influence digital behavioural outcomes. More importantly, the findings indicate that the consequences of digital engagement are not driven by screen exposure alone. Rather, behavioural dependency emerged as the principal mechanism through which digital platform conditions translate into productivity-related consequences. This distinction is particularly important because it suggests that adverse outcomes associated with digital technologies arise less from access itself and more from the behavioural incentives embedded within platform environments.

Building upon these findings, this chapter interprets the results in relation to the study objectives, hypotheses, and existing literature. The discussion evaluates the extent to which the findings support existing theoretical perspectives and considers their implications for understanding the economic consequences of attention-based digital markets. Particular emphasis is placed on the roles of information asymmetry, behavioural dependency, and productivity-related externalities in shaping user outcomes.

The chapter further discusses the theoretical, policy, and practical implications of the findings,

identifies the principal contributions of the study, outlines its limitations, and proposes directions for future research. By moving beyond statistical relationships and focusing on the broader significance of the results, the chapter provides a basis for assessing whether the institutional characteristics of digital attention markets contribute to outcomes that diverge from socially optimal levels of welfare.

5.2 Discussion of Findings

The objective of this study was to examine whether the attention economy generates outcomes consistent with market failure by influencing individual behaviour through Digital Access, Asymmetric Information, Screen Use Intensity, and Screen Addiction. The empirical findings provide evidence that behavioural outcomes associated with digital platforms are shaped not only by technological access but also by the informational architecture within which digital interactions occur.

A central finding of the study is that increased digital participation does not automatically produce adverse outcomes. Rather, the consequences depend on the form that engagement takes. While both Digital Access and Asymmetric Information significantly increased Screen Use Intensity and Screen Addiction, only Screen Addiction emerged as a significant predictor of productivity-related outcomes. This distinction is important because public and policy debates often treat screen exposure and problematic use as equivalent phenomena. The results suggest that such an approach oversimplifies the behavioural processes operating within digital environments.

The findings support the argument advanced by Simon (1971) that abundance of information creates scarcity of attention. In contemporary digital markets, competition increasingly centres on capturing and retaining user attention rather than merely providing information. Consistent with the observations of Davenport and Beck (2001), attention has become a strategic economic resource, and digital platforms employ increasingly sophisticated mechanisms to maximise user engagement. The present findings suggest that these mechanisms influence behavioural outcomes primarily when engagement evolves into dependency-oriented patterns rather than through exposure alone.

The results also provide support for Information Asymmetry Theory. Akerlof (1970) demonstrated that markets may produce inefficient outcomes when one party possesses substantially more information than another. In digital markets, platforms have extensive knowledge regarding user preferences, behavioural patterns, and engagement tendencies, whereas users possess limited information regarding algorithmic processes and attention-optimisation strategies. The significant influence of Asymmetric Information on both Screen Use Intensity and Screen Addiction indicates that informational advantages represent an important mechanism through which platforms shape user behaviour.

From a behavioural economics perspective, the findings further suggest that digital engagement cannot be explained solely through assumptions of fully rational decision-making. As Thaler and Sunstein (2008) argued, individual choices are frequently influenced by environmental cues and choice architecture. The behavioural design features embedded within digital platforms, including personalised recommendations, notifications, infinite scrolling, and algorithmic content curation, may encourage patterns of engagement that diverge from users' long-term welfare interests. The results therefore support the view that behavioural outcomes within digital markets are influenced by both individual preferences and platform design characteristics.

Overall, the findings contribute to the emerging literature on the economic consequences of the attention economy by identifying Screen Addiction as the principal behavioural mechanism through which digital environments influence productivity outcomes. The results suggest that concerns regarding digital technologies should focus less on screen exposure itself and more on the conditions under which engagement develops into dependency-oriented behaviour. This distinction provides an important foundation for understanding how attention-based markets may generate outcomes that differ from socially optimal levels of welfare.

5.2.1 Digital Access and Digital Behaviour

One of the central objectives of this study was to examine how Digital Access influences behavioural outcomes associated with digital platform use. The findings indicate that Digital Access positively

influences both Screen Use Intensity and Screen Addiction. These results suggest that access functions as a necessary precondition for participation in digital environments and creates the opportunity for sustained engagement with platform ecosystems.

The positive relationship between Digital Access and Screen Use Intensity is consistent with the broader literature on technology adoption and digital participation. As digital devices become more affordable, internet connectivity expands, and mobile technologies become increasingly integrated into everyday activities, barriers to participation decline. Van Dijk (2020) argued that access remains a fundamental determinant of digital engagement because it shapes individuals' ability to utilise digital resources and services. The present findings support this argument by demonstrating that individuals with greater access engage more intensively with digital technologies.

However, the findings extend beyond the traditional digital divide literature by demonstrating that Digital Access is also associated with higher levels of Screen Addiction. This result suggests that the consequences of access are not exclusively beneficial. While access facilitates information acquisition, communication, education, and economic participation, it simultaneously increases exposure to platform environments specifically designed to maximise user engagement.

This finding is consistent with the attention economy perspective advanced by Wu (2016), who argued that digital business models increasingly depend on the acquisition and monetisation of user attention. Greater access increases the frequency of interactions between users and digital platforms, thereby creating more opportunities for engagement mechanisms to operate. Repeated exposure to personalised content, notifications, and variable reward structures may gradually reinforce behavioural patterns that become habitual and, in some cases, compulsive.

The relationship can also be interpreted through the lens of behavioural economics. Traditional economic theory assumes that individuals make informed decisions that maximise utility. However, behavioural economists such as Kahneman (2011) have shown that decision-making is often influenced by cognitive biases, limited self-control, and automatic behavioural responses. Digital environments are particularly effective at exploiting these behavioural tendencies because engagement mechanisms operate continuously and adapt to user behaviour over time. Consequently, increased access may not merely expand opportunities for participation; it may also increase exposure to behavioural influences that encourage prolonged engagement.

The findings therefore highlight the dual nature of Digital Access. On one hand, access promotes inclusion, connectivity, and participation in digital markets. On the other hand, it increases exposure to attention-capturing environments that may encourage dependency-oriented behaviour.

From the perspective of the present study, Digital Access should therefore be viewed as an enabling condition rather than a direct source of harm. Access creates the opportunity for engagement, but adverse outcomes emerge only when engagement develops into addictive patterns of behaviour. This distinction helps explain why Digital Access exerts significant effects on Screen Use Intensity and Screen Addiction, while its ultimate consequences depend on the behavioural pathways through which engagement evolves.

5.2.2 Asymmetric Information and Digital Behaviour

One of the most significant findings of this study is the strong influence of Asymmetric Information on both Screen Use Intensity and Screen Addiction. While Digital Access was found to increase digital engagement, the results suggest that informational asymmetries embedded within digital platforms play an even more influential role in shaping user behaviour. This finding shifts attention away from access-based explanations of digital engagement and towards the institutional and informational structures through which engagement is organised.

The result is consistent with the logic of Information Asymmetry Theory. Akerlof (1970) demonstrated that markets may generate inefficient outcomes when one party possesses substantially greater information than another. Although originally developed in the context of product markets, the underlying principle appears highly relevant to contemporary digital environments. Digital platforms possess extensive information regarding user preferences, browsing histories, engagement patterns, and behavioural tendencies, while users typically have limited knowledge regarding recommendation algorithms, data collection practices, and attention-optimisation strategies. This informational imbalance

creates conditions under which platforms can influence behaviour in ways that are not fully transparent to users.

The findings suggest that informational advantages are not merely a feature of digital markets but a mechanism through which user engagement is actively shaped. Modern platforms increasingly rely on predictive analytics, behavioural tracking, and algorithmic curation to determine which content users encounter and how long they remain engaged. As Zuboff (2019) argued, the accumulation of behavioural data has become a central source of economic value in digital markets. The present findings provide empirical support for this argument by demonstrating that greater perceived informational asymmetry is associated with both higher engagement intensity and stronger tendencies towards addictive usage patterns.

Particularly noteworthy is the finding that Asymmetric Information exerts a stronger influence on Screen Addiction than Digital Access. This suggests that problematic digital behaviour cannot be explained solely by the availability of technology. Instead, addiction appears to be linked to the way digital environments are structured and managed. Users may enter digital platforms because they have access, but the persistence of engagement appears increasingly influenced by platform-controlled mechanisms that continuously adapt to individual behavioural responses.

This finding also contributes to the attention economy literature. Simon (1971) argued that an abundance of information inevitably creates scarcity of attention. Subsequent scholars such as Davenport and Beck (2001) and Wu (2016) suggested that competition in digital markets increasingly revolves around capturing and retaining user attention. The present study extends this argument by indicating that informational asymmetries constitute one of the mechanisms through which attention is secured and monetised. Rather than competing solely on content quality or service provision, platforms may utilise informational advantages to influence how attention is allocated and sustained.

From a broader economic perspective, the findings provide support for the argument that attention-based markets may generate outcomes that diverge from socially optimal levels of welfare. When users lack full information regarding how engagement is engineered and monetised, behavioural outcomes may reflect platform incentives as much as individual preferences. This observation strengthens the view that informational asymmetry represents a potential source of market inefficiency in digital environments.

Overall, the findings suggest that Asymmetric Information should be viewed as a central structural characteristic of contemporary digital markets. While Digital Access creates opportunities for participation, informational asymmetries appear to influence how attention is directed, sustained, and transformed into behavioural outcomes. The results therefore highlight the importance of incorporating informational power into economic analyses of digital engagement and contribute to a growing body of research examining the behavioural consequences of the attention economy.

5.2.3 Impact of Screen Use Intensity on Productivity and Mental Hygiene

One of the most noteworthy findings of the study is the absence of a significant relationship between Screen Use Intensity and either Impact on Productivity or Mental Hygiene. Although Digital Access and Asymmetric Information were found to increase Screen Use Intensity, the results indicate that greater engagement with digital technologies does not necessarily translate into adverse economic or psychological outcomes. This finding challenges a widely held assumption in public discourse that increased screen time is inherently harmful.

The result suggests that the quantity of digital engagement alone is insufficient to explain variations in productivity or mental well-being. Much of the contemporary debate surrounding digital technologies implicitly assumes a direct relationship between screen exposure and negative outcomes. However, the findings of the present study indicate that such a relationship may be more complex than is often assumed. Individuals use digital technologies for a wide range of purposes, including education, professional work, information acquisition, communication, entertainment, and social interaction. Consequently, increased screen engagement may generate both benefits and costs, making its overall effect dependent on the nature of usage rather than its duration alone.

This finding is consistent with emerging research questioning the tendency to treat screen time as

a universal measure of digital harm. Orben and Przybylski (2019) argued that the relationship between digital technology use and well-being is often weaker and more context-dependent than suggested by popular narratives. Similarly, Valkenburg et al. (2022) observed that the effects of digital engagement vary considerably across individuals and depend on how technologies are used rather than simply how much they are used. The present findings provide further evidence that screen exposure, by itself, may not be an adequate indicator of adverse outcomes.

From a behavioural perspective, the result highlights the importance of distinguishing between intensive use and problematic use. Individuals may spend substantial amounts of time online without experiencing meaningful reductions in productivity or deterioration in mental well-being, provided that their engagement remains purposeful and under voluntary control. Screen Use Intensity captures the extent of digital engagement, but it does not necessarily capture the psychological processes associated with compulsion, loss of self-regulation, or dependency. As a result, high levels of engagement may coexist with positive educational, occupational, and social outcomes.

The finding also has important implications for Attention Economy Theory. Much of the literature has focused on the increasing ability of digital platforms to attract and retain user attention. However, the present results suggest that the allocation of attention is not inherently problematic. Rather, the consequences depend on how that attention is utilised and whether engagement remains consistent with users' long-term interests and objectives. In this sense, attention itself should not be viewed as the source of welfare loss. Instead, adverse outcomes appear to arise when attention becomes captured in ways that reduce individual autonomy and encourage dependency-oriented behaviour.

Importantly, the non-significant relationship between Screen Use Intensity and both outcome variables strengthens the interpretation of subsequent findings relating to Screen Addiction. If screen exposure alone does not significantly influence productivity or mental well-being, then the negative consequences observed elsewhere in the model cannot be attributed simply to time spent online. Instead, they appear to emerge through behavioural mechanisms associated with addictive engagement. This distinction represents one of the key contributions of the study because it shifts the focus from exposure-based explanations towards dependency-based explanations of digital harm.

From a policy perspective, the findings suggest that interventions aimed solely at reducing screen time may be insufficient. Policies based exclusively on limiting exposure risk overlooking the behavioural processes that generate adverse outcomes. Greater emphasis may therefore be placed on promoting healthy patterns of digital engagement, improving digital literacy, and addressing platform design features that encourage compulsive use. Such an approach is likely to be more effective than treating all forms of digital engagement as equally problematic.

Overall, the findings indicate that Screen Use Intensity is not a significant predictor of either Productivity Loss or Mental Hygiene. The results therefore suggest that the adverse consequences associated with digital technologies cannot be explained by exposure alone. Instead, the evidence points towards behavioural dependency as the more relevant mechanism linking digital environments to economic and psychological outcomes.

Impact of Screen Addiction on Productivity and Mental Hygiene

A central finding of the study is that Screen Addiction emerged as the most influential behavioural construct within the proposed framework. Unlike Screen Use Intensity, which did not significantly affect either outcome variable, Screen Addiction exhibited a strong positive relationship with Impact on Productivity ($\beta = 0.733$, $p < 0.001$). This finding suggests that the adverse consequences associated with digital engagement are linked less to the amount of time spent using digital technologies and more to the development of dependency-oriented patterns of behaviour.

The strong association between Screen Addiction and productivity outcomes can be interpreted through the lens of behavioural economics and attention allocation. Productivity depends not only on the quantity of time available but also on the ability to allocate attention efficiently across competing tasks. Individuals exhibiting addictive digital behaviours are more likely to engage in compulsive checking, persistent multitasking, habitual platform switching, and repeated interruptions. These behaviours fragment attention and increase cognitive switching costs, thereby reducing the ability to sustain concentration on productive activities. As Davenport and Beck (2001) argued, attention constitutes a scarce economic resource, and inefficient allocation of attention can generate significant performance costs.

The present findings provide empirical support for this argument by demonstrating that dependency-oriented digital engagement is associated with measurable productivity-related consequences.

The result is also consistent with the broader literature on problematic technology use. Previous studies have reported that compulsive digital engagement is associated with lower academic performance, workplace inefficiency, procrastination, and diminished task completion capabilities. The findings therefore support the view that behavioural dependency represents a key mechanism through which digital environments influence economic outcomes. Importantly, the effect size analysis presented in Chapter 4 identified Screen Addiction as the strongest predictor in the entire structural model, further highlighting its central role in explaining productivity-related variation.

In contrast, Screen Addiction did not exhibit a statistically significant relationship with Mental Hygiene ($\beta = 0.154$, $p = 0.172$). Although the direction of the relationship was positive, the absence of statistical significance suggests that addictive digital behaviour alone may not be sufficient to explain differences in psychological well-being among respondents. This finding is noteworthy because much of the contemporary discourse surrounding digital technologies assumes a direct connection between problematic digital use and mental health deterioration.

One possible explanation is that mental hygiene is influenced by a much broader set of determinants than productivity. Factors such as personality characteristics, family environment, social relationships, coping mechanisms, academic pressures, workplace stress, and socio-economic conditions may exert a stronger influence on psychological well-being than digital behaviour alone. Consequently, while screen addiction may contribute to psychological strain in some contexts, its independent explanatory power appears limited when these broader influences are taken into account.

The finding also highlights the importance of avoiding deterministic interpretations of digital technology use. Not all individuals who exhibit signs of intensive or problematic engagement necessarily experience adverse psychological outcomes. Some users may possess stronger self-regulation mechanisms, greater emotional resilience, or supportive social environments that mitigate potential negative effects. The relationship between digital behaviour and mental well-being may therefore be contingent upon contextual and individual-level factors that were not incorporated into the present model.

From a theoretical perspective, the contrasting results for Productivity and Mental Hygiene refine our understanding of the mechanisms through which the attention economy generates welfare consequences. The findings suggest that behavioural dependency produces more immediate and observable effects on productivity than on psychological well-being. Productivity losses arise directly from the misallocation of attention and time, whereas mental hygiene appears to be influenced by a wider and more complex set of interacting factors.

Overall, the results identify Screen Addiction as the principal behavioural pathway linking digital engagement to productivity-related outcomes. At the same time, the absence of a significant relationship with Mental Hygiene suggests that the consequences of addictive digital behaviour may be more economically observable than psychologically universal. This distinction strengthens the central argument of the study that the costs associated with the attention economy arise primarily through behavioural dependency and inefficient attention allocation rather than through digital exposure alone.

Productivity Outcomes in the Attention Economy

Productivity constitutes one of the most important economic outcomes examined in this study because it directly reflects how individuals allocate scarce cognitive resources across competing activities. The findings indicate that Digital Access, Asymmetric Information, and Screen Addiction collectively shape productivity outcomes, although their effects operate through different mechanisms.

A key contribution of the study is the identification of Screen Addiction as the principal behavioural pathway linking digital environments to productivity-related consequences. While Digital Access expands opportunities for participation in digital ecosystems and Asymmetric Information influences user behaviour through platform-driven engagement mechanisms, the results suggest that productivity losses emerge primarily when engagement develops into dependency-oriented behaviour. This finding reinforces the distinction between digital participation and problematic digital consumption.

The mediation analysis provides further insight into this relationship. Both Digital Access and Asymmetric Information exert significant indirect effects on Impact on Productivity through Screen Addiction, indicating that a substantial proportion of productivity-related consequences is transmitted

through behavioural dependency. In contrast, Screen Use Intensity did not significantly mediate productivity outcomes. This distinction suggests that productivity losses cannot be explained simply by the amount of time spent using digital technologies. Rather, adverse outcomes arise when engagement becomes compulsive and begins to interfere with attention management and task performance.

From an economic perspective, the findings can be interpreted through the concept of attention as a scarce resource. Simon (1971) argued that an abundance of information creates a scarcity of attention because individuals possess limited cognitive capacity to process competing stimuli. Similarly, Davenport and Beck (2001) described attention as an increasingly valuable economic resource in information-rich environments. The present findings support these arguments by demonstrating that productivity-related costs emerge when digital engagement persistently competes for and captures user attention.

The results may also be understood through the concept of opportunity cost. Time and cognitive effort devoted to compulsive digital engagement inevitably reduce the resources available for alternative activities such as work, education, learning, and skill development. Consequently, the productivity losses associated with Screen Addiction represent not merely individual behavioural outcomes but also forgone economic opportunities. In this sense, digital platforms compete not only for consumer expenditure but also for finite cognitive resources.

The findings therefore provide important evidence for understanding the economic consequences of the attention economy. When platform incentives encourage behavioural patterns that reduce productive activity, private benefits generated through increased engagement may diverge from broader welfare outcomes. This divergence is consistent with the notion that attention-based digital markets can generate external costs that are not fully reflected in market transactions.

Overall, the results suggest that productivity-related consequences arise less from digital access or screen exposure itself and more from the development of addictive engagement patterns. The findings therefore identify Screen Addiction as the primary mechanism through which attention-based digital environments influence individual economic performance.

Mental Hygiene Outcomes in the Attention Economy

The findings relating to Mental Hygiene present a more nuanced picture than those observed for productivity outcomes. Unlike productivity, which was significantly influenced by Screen Addiction, neither Screen Use Intensity nor Screen Addiction emerged as significant predictors of Mental Hygiene. Furthermore, the mediation analysis did not identify any significant indirect pathways linking Digital Access or Asymmetric Information to Mental Hygiene through the behavioural mechanisms included in the model.

These findings suggest that the relationship between digital engagement and psychological well-being is substantially more complex than the relationship between digital engagement and productivity. Productivity losses can arise relatively directly through distraction, interruptions, and inefficient allocation of attention. Mental well-being, however, reflects a broader set of psychological, social, and environmental influences that extend beyond digital behaviour alone. Consequently, the explanatory power of digital engagement variables may be more limited when examining mental hygiene outcomes.

One possible interpretation is that digital technologies generate both beneficial and adverse psychological effects simultaneously. While excessive engagement may contribute to stress, information overload, or emotional fatigue, digital platforms can also provide social connection, informational support, entertainment, and opportunities for community participation. These competing influences may offset one another, resulting in weaker aggregate effects on mental well-being. The findings therefore suggest that digital engagement cannot be assumed to produce uniformly negative psychological outcomes.

The results are consistent with recent research emphasising that the relationship between digital technology use and well-being is often modest and highly context dependent. Orben and Przybylski (2019) argued that the association between digital technology use and psychological well-being is considerably weaker than frequently portrayed in public debate. Similarly, Valkenburg et al. (2022) observed that the effects of digital engagement vary substantially across individuals and depend on personal characteristics, patterns of use, and contextual factors. The present findings provide further support for this perspective by indicating that digital behaviour alone is insufficient to explain variation

in mental hygiene outcomes.

The absence of significant mediation effects also suggests that the mechanisms influencing mental well-being differ from those influencing productivity. Whereas productivity appears sensitive to behavioural dependency and attention misallocation, mental hygiene may be shaped more strongly by factors such as emotional resilience, social support, family relationships, educational pressures, occupational stress, and broader life circumstances. As a result, the pathways linking digital engagement to psychological outcomes may be more indirect and contingent than those affecting economic performance.

From the perspective of the attention economy, these findings indicate that the consequences of attention capture are more readily observable in productivity-related outcomes than in mental well-being outcomes. This distinction is theoretically important because it suggests that the welfare implications of digital markets should not be assessed solely through psychological indicators. The economic costs associated with attention diversion and behavioural dependency may be more immediate and measurable than their psychological consequences.

Overall, the findings suggest that the attention economy exerts a clearer influence on productivity than on Mental Hygiene. While behavioural dependency contributes significantly to productivity-related costs, its effects on psychological well-being appear less direct and more dependent on contextual factors beyond those captured in the present framework. This distinction contributes to a more balanced understanding of digital engagement by recognising that economic and psychological consequences may emerge through different mechanisms and with differing levels of intensity.

Mediation through Screen Use Intensity

One of the most theoretically important findings of the study is the absence of a significant mediating role for Screen Use Intensity. Although both Digital Access and Asymmetric Information significantly increased Screen Use Intensity, none of the indirect pathways operating through this construct were statistically significant. Consequently, the results provide no evidence that Screen Use Intensity functions as a mechanism linking digital market conditions to either Productivity Loss or Mental Hygiene.

This finding challenges a common assumption in discussions of digital technology use, namely that greater screen exposure inevitably produces adverse outcomes. While increased access and platform-driven engagement encourage individuals to spend more time within digital environments, the results suggest that the quantity of engagement alone is insufficient to explain variations in productivity or psychological well-being. Individuals may spend substantial amounts of time online for educational, professional, informational, or social purposes without necessarily experiencing negative consequences.

The finding is consistent with emerging research questioning the use of screen time as a universal indicator of digital harm. Orben and Przybylski (2019) argued that the relationship between digital technology use and well-being is often considerably weaker than suggested by public discourse. Similarly, Valkenburg et al. (2022) emphasised that the effects of digital engagement depend on how technologies are used rather than merely the amount of time spent online. The present findings extend this argument by demonstrating that Screen Use Intensity does not constitute a significant pathway through which Digital Access or Asymmetric Information influence individual outcomes.

From the perspective of the attention economy, the results suggest that attention allocation is not inherently harmful. Digital platforms undoubtedly compete for user attention, but welfare losses appear to depend on the behavioural nature of engagement rather than its duration. The distinction between intensive use and problematic use is therefore critical. Intensive use reflects the extent of engagement, whereas problematic use reflects a loss of behavioural control. The findings indicate that adverse outcomes are more closely associated with the latter than the former.

Overall, the absence of significant mediation through Screen Use Intensity suggests that screen exposure alone does not represent the principal mechanism through which the attention economy affects individual welfare. This finding refines existing discussions by shifting attention away from screen time as a standalone concern and towards the behavioural processes that govern digital engagement.

Mediation through Screen Addiction

In contrast to Screen Use Intensity, Screen Addiction emerged as a significant mediating mechanism within the proposed framework. The mediation analysis demonstrated that Screen Addiction significantly transmitted the effects of both Digital Access and Asymmetric Information to Impact on Productivity. These findings indicate that the influence of digital market conditions on productivity operates not only through direct pathways but also through behavioural dependency generated within digital environments.

The significant indirect effects suggest that Digital Access and Asymmetric Information influence productivity partly by increasing the likelihood of addictive engagement. More importantly, the mediation analysis revealed evidence of complementary partial mediation, indicating that both direct and indirect effects remain significant. This finding implies that productivity-related consequences arise through multiple channels simultaneously, with Screen Addiction representing an important but not exclusive mechanism.

The theoretical significance of this result lies in its identification of behavioural dependency as the key transmission mechanism linking digital environments to economic outcomes. Unlike Screen Use Intensity, which captures the extent of engagement, Screen Addiction reflects compulsive usage patterns, impaired self-regulation, and persistent difficulty disengaging from digital platforms. These characteristics directly affect an individual's capacity to allocate attention efficiently and sustain productive activity.

The findings are consistent with behavioural economic perspectives that emphasise bounded rationality and self-control limitations in decision-making. Digital platforms increasingly employ personalised recommendations, intermittent rewards, notifications, algorithmic content curation, and social validation mechanisms that encourage repeated engagement. As users become increasingly dependent on these reward structures, attention is progressively diverted from alternative productive activities. Consequently, productivity losses emerge not because individuals participate in digital environments, but because engagement evolves into dependency-oriented behaviour.

From the perspective of Attention Economy Theory, Screen Addiction represents the mechanism through which platform incentives are translated into individual-level consequences. Davenport and Beck (2001) argued that attention functions as a scarce economic resource, while Simon (1971) highlighted the challenges created by information abundance. The present findings provide empirical support for these arguments by demonstrating that productivity-related costs arise when digital platforms successfully capture and retain attention beyond users' intended levels of engagement.

The mediation results therefore strengthen the central argument of the study. The adverse consequences associated with the attention economy do not arise merely because individuals spend more time online. Rather, they emerge when platform structures encourage behavioural dependency that interferes with effective attention allocation and productive activity. Screen Addiction thus functions as the principal behavioural pathway through which digital market conditions generate economic costs.

Moderating Role of Asymmetric Information

The moderation analysis provides important insights into how platform-level informational advantages shape user behaviour within digital markets. The results indicate that Asymmetric Information significantly moderates the relationship between Digital Access and Screen Use Intensity, but does not moderate the relationship between Digital Access and Screen Addiction. This differentiated pattern suggests that informational asymmetry influences certain dimensions of digital behaviour while leaving others largely unaffected.

The significant negative interaction effect observed for Screen Use Intensity indicates that the positive relationship between Digital Access and engagement weakens as informational asymmetry increases. This finding suggests that access and informational power perform distinct functions within digital ecosystems. Digital Access determines the opportunity to participate in digital environments, whereas Asymmetric Information reflects the capacity of platforms to understand, predict, and influence user behaviour through the collection and analysis of behavioural data.

From the perspective of Information Asymmetry Theory, the result implies that user engagement is increasingly shaped by platform intelligence rather than by access alone. Akerlof (1970) argued that

information asymmetries alter market outcomes by creating imbalances in knowledge between market participants. In digital environments, platforms possess extensive information regarding user preferences, browsing behaviour, engagement histories, and consumption patterns, while users typically have limited knowledge regarding the functioning of recommendation systems and attention-optimisation algorithms. As a result, engagement decisions are not determined solely by individual preferences but are increasingly influenced by platform-directed behavioural architectures.

The finding is also consistent with the broader literature on the attention economy. Davenport and Beck (2001) argued that attention has become a scarce economic resource, while Wu (2016) demonstrated that digital platforms increasingly compete through mechanisms designed to capture and retain user attention. The present results extend these arguments by suggesting that informational advantages allow platforms to reduce the relative importance of access in determining engagement. Once individuals are embedded within highly personalised digital environments, algorithmic systems increasingly guide content exposure and attention allocation, thereby diminishing the marginal contribution of Digital Access to engagement intensity.

In contrast, the interaction effect between Asymmetric Information and Digital Access on Screen Addiction was not statistically significant. This finding suggests that although both Digital Access and Asymmetric Information independently contribute to addictive behaviour, informational asymmetry does not alter the strength of the relationship between access and addiction. The development of Screen Addiction therefore appears to follow a different behavioural process than Screen Use Intensity.

A plausible explanation is that addiction is driven primarily by psychological mechanisms such as reinforcement learning, habit formation, reward anticipation, and compulsive behavioural patterns. Once these processes become established, their influence may operate relatively independently of variations in informational asymmetry. In other words, informational advantages may help platforms attract and retain attention, but the transition from engagement to addiction appears to depend more heavily on behavioural and psychological factors than on informational conditions alone.

This distinction has important implications for understanding platform power. The findings suggest that informational asymmetry is particularly effective in shaping engagement behaviour, but less effective in explaining the emergence of addictive behaviour. While platforms can influence how attention is allocated through algorithmic systems and personalised content delivery, addiction appears to reflect a deeper behavioural response that cannot be fully explained by informational advantages alone.

Overall, the moderation results reinforce the argument that informational asymmetry constitutes a key structural feature of the attention economy. The findings indicate that platform power extends beyond information provision and increasingly involves the capacity to predict, shape, and monetise user attention. At the same time, the absence of moderation for Screen Addiction highlights the importance of distinguishing between engagement and dependency. This distinction contributes to a more nuanced understanding of how digital platforms influence behaviour and clarifies the mechanisms through which attention-based markets may generate welfare-relevant outcomes.

5.3 Theoretical Implications

The findings of this study contribute to the literature on the Attention Economy, Information Asymmetry, Behavioural Economics, and Market Failure by identifying the mechanisms through which digital market conditions influence individual outcomes. A central contribution of the study is the distinction between digital engagement and digital dependency. While Digital Access and Asymmetric Information increase both Screen Use Intensity and Screen Addiction, only Screen Addiction emerged as a significant pathway linking digital environments to adverse productivity outcomes. This finding suggests that the consequences of the attention economy arise not from digital participation itself but from the development of dependency-oriented patterns of engagement.

5.3.1 Implications for Attention Economy Theory

The findings provide empirical support for the proposition that attention has become a scarce economic resource in information-rich environments, as argued by Simon (1971), Goldhaber (1997), and Daven-

port and Beck (2001). Digital Access and Asymmetric Information were found to increase engagement with digital platforms, indicating that attention remains the primary object of competition in contemporary digital markets.

However, the study extends Attention Economy Theory by demonstrating that attention capture alone is insufficient to explain welfare-relevant outcomes. Screen Use Intensity did not significantly affect Productivity or Mental Hygiene, whereas Screen Addiction emerged as a significant predictor of productivity-related consequences. This finding suggests that the adverse effects of the attention economy arise when attention capture evolves into behavioural dependency rather than from engagement itself.

The moderation results provide an additional contribution by showing that informational advantages weaken the role of Digital Access in determining engagement intensity. This finding indicates that platform power increasingly derives from the ability to direct and monetise attention through algorithmic systems rather than merely providing access to information. Consequently, the study refines Attention Economy Theory by highlighting the distinction between attention acquisition and attention dependence.

5.3.2 Implications for Information Asymmetry Theory

The study extends Information Asymmetry Theory into the context of digital behavioural outcomes. Akerlof (1970) originally conceptualised information asymmetry as a source of inefficiency in market transactions. The present findings suggest that informational advantages in digital markets influence not only economic exchanges but also patterns of attention allocation and behavioural engagement.

Asymmetric Information exerted stronger effects on Screen Use Intensity and Screen Addiction than Digital Access, indicating that platform-held information functions as an active determinant of behaviour rather than a passive market characteristic. Through data collection, behavioural analytics, and personalised recommendation systems, digital platforms acquire informational advantages that allow them to influence engagement more effectively.

The moderation findings further demonstrate that informational asymmetry shapes how Digital Access translates into engagement behaviour. At the same time, the absence of a significant moderation effect for Screen Addiction suggests that informational advantages alone cannot fully explain behavioural dependency. This finding refines Information Asymmetry Theory by indicating that informational power interacts with psychological and behavioural processes rather than operating as a complete explanation of digital addiction.

5.3.3 Implications for Behavioural Economics

The findings provide support for behavioural economic perspectives that challenge assumptions of fully rational decision-making. The distinction between Screen Use Intensity and Screen Addiction suggests that digital behaviour cannot be understood solely through models based on stable preferences and utility maximisation.

The significant mediating role of Screen Addiction indicates that productivity-related consequences emerge when users experience diminished self-regulation and behavioural dependency. This finding is consistent with Simon's (1955) concept of bounded rationality and with behavioural economic arguments concerning limited self-control and decision-making biases.

The results also highlight the role of platform design in shaping behaviour. Features such as personalised recommendations, notifications, social validation mechanisms, and algorithmic content delivery influence attention allocation in ways that may not fully reflect user intentions. Consequently, the study extends Behavioural Economics into the domain of digital markets by demonstrating how behavioural biases and platform incentives interact to influence engagement outcomes.

5.3.4 Implications for Market Failure Theory

The study provides theoretical support for the argument that attention-based digital markets exhibit characteristics associated with market failure. Traditional market failure theory identifies information

asymmetry and externalities as sources of inefficient outcomes (Stiglitz, 1989; Varian, 2014). The findings indicate that both mechanisms are relevant within the attention economy.

First, the significant effects of Asymmetric Information on engagement and addiction demonstrate that digital markets are characterised by substantial informational imbalances between platforms and users. Second, the productivity-related consequences associated with Screen Addiction suggest the presence of negative externalities. While platforms benefit from prolonged engagement, the resulting productivity costs are borne primarily by users.

Importantly, the findings indicate that market failure arises not from digital participation itself but from platform incentives that encourage dependency-oriented engagement. This distinction contributes to Market Failure Theory by demonstrating that welfare losses in digital markets emerge through behavioural mechanisms rather than through information consumption alone.

Overall, the study suggests that attention should be viewed as an economic resource subject to strategic capture and monetisation. The interaction between informational advantages, behavioural responses, and platform incentives creates conditions under which private benefits may diverge from broader welfare outcomes. As a result, understanding digital market performance requires theoretical frameworks that integrate informational and behavioural dimensions alongside traditional economic considerations.

5.4 Economic Implications

The findings of this study have important implications for understanding the economic consequences of attention-based digital markets. While digital platforms generate substantial benefits through improved connectivity, information access, and technological innovation, the results indicate that attention-driven business models may also create costs that are not fully reflected in market transactions. In particular, the findings suggest that productivity-related welfare losses arise primarily through behavioural dependency rather than digital participation itself. These results contribute to ongoing debates concerning the allocation of attention, the role of informational power in digital markets, and the efficiency of platform-based economic systems.

5.4.1 Productivity Costs of the Attention Economy

One of the most important economic implications of the study concerns productivity. The findings indicate that productivity losses are associated with Screen Addiction rather than Screen Use Intensity. This distinction suggests that the economic costs of digital engagement arise not from technology use per se but from behavioural patterns that interfere with effective attention allocation.

From an economic perspective, productivity depends upon the efficient use of scarce resources, including time, effort, and cognitive capacity. When attention becomes persistently diverted towards compulsive digital engagement, fewer resources remain available for educational, professional, and productive activities. Consequently, the productivity losses associated with behavioural dependency represent an economic cost that extends beyond individual users and may affect organisational performance and broader economic efficiency.

The findings support the argument that attention has become an increasingly important factor of economic performance. As digital platforms compete to capture and retain user engagement, the opportunity cost of attention becomes more significant. Time devoted to dependency-oriented engagement displaces alternative activities that may generate greater personal or economic value. The results therefore suggest that productivity losses constitute one of the most tangible economic consequences of the attention economy.

5.4.2 Attention as an Economic Resource

The study reinforces the growing recognition of attention as a scarce economic resource. Simon (1971) argued that information abundance inevitably creates attention scarcity because individuals possess limited cognitive capacity to process information. Goldhaber (1997) subsequently proposed that attention

functions as a form of economic currency in digital environments, while Davenport and Beck (2001) described attention as a strategic resource over which firms increasingly compete.

The findings provide empirical support for these arguments. Both Digital Access and Asymmetric Information significantly influenced digital engagement, indicating that user attention remains the primary resource around which digital business models are organised. Unlike conventional resources, attention is inherently finite; attention allocated to one activity cannot simultaneously be allocated elsewhere. Consequently, competition for attention creates important opportunity costs that affect productivity, learning, and decision-making.

The results suggest that contemporary digital markets increasingly operate as systems for attention allocation rather than merely information distribution. Economic value is generated not simply through providing information but through attracting, retaining, and monetising user attention. This shift has important implications for understanding consumer behaviour and market performance in the digital economy.

5.4.3 Welfare Implications of Behavioural Dependency

The findings also raise important questions regarding welfare within digital markets. Conventional economic models assume that individuals make choices that maximise utility based on informed preferences. However, the significant role of Screen Addiction suggests that observed engagement may not always reflect welfare-maximising behaviour.

The mediation analysis demonstrated that behavioural dependency constitutes the primary pathway through which Digital Access and Asymmetric Information influence productivity outcomes. This finding implies that users may continue engaging with digital platforms despite experiencing adverse consequences in terms of time management, attention allocation, and productive performance.

Behavioural economics offers a useful framework for interpreting this outcome. Simon (1955) emphasised bounded rationality in decision-making, while Thaler and Sunstein (2008) demonstrated how behavioural choices are influenced by choice architecture and self-control limitations. Digital platforms increasingly utilise personalised recommendations, notifications, intermittent rewards, and other persuasive design features that influence engagement behaviour. Under such conditions, higher engagement levels may not necessarily correspond to higher welfare levels.

The findings therefore suggest that welfare in digital markets should not be evaluated solely through measures of participation or usage. Instead, attention should be given to the quality of engagement and the extent to which engagement reflects autonomous rather than dependency-oriented behaviour. This distinction has important implications for evaluating the social consequences of attention-based business models.

5.4.4 Information Asymmetry and Market Efficiency

The study further highlights the economic significance of information asymmetry in digital markets. Asymmetric Information exerted stronger effects on digital behaviour than Digital Access, indicating that informational advantages constitute an important source of platform power.

Akerlof (1970) demonstrated that information asymmetries can generate inefficient market outcomes when one party possesses substantially greater information than another. The present findings suggest that similar dynamics operate in digital environments. Platforms possess extensive information regarding user preferences, behavioural patterns, and engagement histories, whereas users typically possess limited knowledge regarding algorithmic processes, data utilisation practices, and content curation mechanisms.

The moderation results further indicate that informational advantages influence how access translates into engagement. As informational asymmetry increases, engagement becomes increasingly shaped by platform-controlled mechanisms rather than by access alone. This finding suggests that informational power affects not only market transactions but also the allocation of attention itself.

From the perspective of market efficiency, these results raise important concerns. When users lack complete information regarding how engagement is influenced, observed behavioural outcomes may not fully reflect informed preferences. Consequently, market outcomes may diverge from those predicted

by conventional models of consumer sovereignty and efficient choice.

Overall, the findings suggest that informational asymmetry represents a significant challenge to efficient market functioning in digital environments. By influencing engagement patterns, behavioural outcomes, and productivity-related consequences, informational advantages become an important determinant of welfare and economic performance within the attention economy.

5.5 Policy Implications

The findings of this study have important implications for regulators, educational institutions, employers, and digital platform providers. A central conclusion emerging from the analysis is that the adverse consequences associated with digital engagement arise primarily through behavioural dependency rather than screen exposure alone. Consequently, policy responses that focus exclusively on reducing screen time are unlikely to address the underlying mechanisms responsible for productivity-related welfare losses. Instead, effective policy interventions must address the structural and behavioural conditions that encourage addictive engagement while simultaneously reducing informational imbalances between users and digital platforms.

5.5.1 Platform Transparency and Algorithmic Accountability

The significant influence of Asymmetric Information on both Screen Use Intensity and Screen Addiction highlights the need for greater transparency in platform operations. Digital platforms possess extensive information regarding user preferences, behavioural patterns, and engagement histories, whereas users typically possess limited knowledge regarding the functioning of recommendation systems, content ranking mechanisms, and behavioural targeting practices.

The findings suggest that informational asymmetry is not merely a market characteristic but an active determinant of user behaviour. Consequently, regulatory efforts should prioritise transparency regarding algorithmic decision-making, data collection practices, and content recommendation systems. Greater disclosure can improve user awareness and reduce the informational imbalance that currently characterises many digital markets.

Policy initiatives aimed at algorithmic accountability may strengthen user autonomy by enabling individuals to make more informed decisions regarding their digital engagement. Such measures are likely to improve market functioning by reducing the gap between platform knowledge and user understanding.

5.5.2 Digital Well-Being and Responsible Platform Design

The results indicate that Screen Addiction, rather than Screen Use Intensity, is the principal mechanism through which productivity-related costs emerge. This finding suggests that policy discussions should move beyond screen-time reduction and focus more directly on the behavioural architecture of digital platforms.

Digital environments increasingly incorporate engagement-maximising features such as infinite scrolling, personalised recommendations, variable reward structures, autoplay functions, and persistent notifications. While these features enhance engagement, they may also encourage dependency-oriented behaviour. The findings therefore support the adoption of digital well-being standards that promote responsible platform design.

Potential measures include enhanced user control over notifications, transparent engagement metrics, optional usage reminders, and default settings that support healthier patterns of digital interaction. Such interventions would preserve the benefits of digital technologies while reducing the likelihood that engagement evolves into behavioural dependency.

5.5.3 Reducing Information Asymmetry in Digital Markets

The significant role of Asymmetric Information within the proposed framework suggests that improving information disclosure should be a central policy priority. Information asymmetry has long been recognised as a source of market inefficiency because it limits the ability of individuals to make informed choices (Akerlof, 1970).

In digital markets, users often lack clear information regarding how behavioural data are collected, processed, and monetised. The findings indicate that these informational imbalances influence engagement behaviour and contribute to outcomes that may not fully reflect informed user preferences.

Policy measures such as simplified privacy disclosures, transparent consent mechanisms, clearer data-use policies, and greater user access to personal behavioural data may help reduce these informational disadvantages. While such measures may not eliminate platform influence entirely, they can improve decision-making conditions and strengthen consumer autonomy within digital environments.

5.5.4 Educational and Digital Literacy Initiatives

The findings also highlight the importance of educational interventions. Since behavioural dependency emerged as the primary source of adverse outcomes, policy responses should focus not only on technology access but also on developing users' capacity to manage digital engagement effectively.

Educational institutions can contribute by incorporating digital literacy and digital well-being programmes into existing curricula. Beyond technical competencies, such programmes should emphasise attention management, algorithmic awareness, persuasive platform design, and self-regulation strategies. Increased awareness of how digital platforms compete for attention may strengthen users' ability to make deliberate and informed engagement decisions.

These interventions may be particularly valuable for younger users, who are often exposed to digital platforms during formative stages of behavioural development.

5.5.5 Workplace and Institutional Policies

The strong relationship between Screen Addiction and productivity loss also carries important implications for organisations. As workplaces become increasingly digitised, concerns relating to attention fragmentation, continuous connectivity, and digital distraction are becoming more relevant to organisational performance.

The findings suggest that employers should view attention management as an important component of productivity enhancement. Policies encouraging focused work periods, reducing unnecessary digital interruptions, establishing communication norms, and promoting digital well-being practices may help mitigate the productivity costs associated with dependency-oriented engagement.

Similarly, educational institutions may benefit from initiatives that support balanced technology use and strengthen students' ability to manage competing attentional demands. Such measures are likely to improve both individual outcomes and institutional effectiveness.

Overall, the policy implications of this study suggest that addressing the challenges of the attention economy requires a combination of transparency measures, behavioural safeguards, educational initiatives, and institutional reforms. The findings indicate that the central policy challenge is not excessive screen exposure itself but the emergence of behavioural dependency within highly information-asymmetric digital environments. Consequently, policy frameworks should focus on promoting informed engagement, strengthening user autonomy, and reducing the productivity-related welfare costs associated with attention-based business models. "'latex

5.6 Contributions of the Study

The present study contributes to the emerging literature on the attention economy by developing and empirically testing an integrated framework linking Digital Access, Asymmetric Information, Screen Use Intensity, Screen Addiction, Impact on Productivity, and Mental Hygiene. By combining perspectives from Attention Economy Theory, Information Asymmetry Theory, Behavioural Economics, and Market

Failure Theory, the study advances understanding of the behavioural and economic mechanisms through which digital platforms influence user outcomes. The contributions of the study may be classified as theoretical, methodological, and empirical.

5.6.1 Theoretical Contributions

The study makes several contributions to the theoretical literature on digital markets and the attention economy.

First, it advances Attention Economy Theory by demonstrating that adverse outcomes are associated primarily with Screen Addiction rather than Screen Use Intensity. While much of the existing discourse treats screen exposure as the principal source of harm, the findings suggest that behavioural dependency provides a more relevant explanation for productivity-related consequences. The study therefore contributes to a clearer conceptual distinction between digital engagement and problematic digital consumption.

Second, the study extends Information Asymmetry Theory into the context of attention-based digital markets. The findings indicate that informational advantages possessed by platforms significantly influence both engagement intensity and addictive behaviour. This broadens the traditional application of information asymmetry beyond product and transaction markets and highlights its relevance in shaping behavioural outcomes.

Third, the study contributes to Behavioural Economics by providing evidence that digital engagement is influenced by behavioural mechanisms that extend beyond conventional assumptions of fully informed and rational decision-making. The findings support the view that platform design, behavioural nudges, and informational advantages play an important role in shaping attention allocation and engagement patterns.

Finally, the study contributes to the emerging literature on digital market failure by providing empirical support for the argument that informational asymmetries and addiction-driven engagement may generate welfare losses that are not fully reflected in market transactions. The findings therefore provide a behavioural perspective on how market inefficiencies may arise within attention-based digital environments.

5.6.2 Methodological Contributions

The study also makes several methodological contributions.

First, it develops and validates a multidimensional framework that simultaneously incorporates Digital Access, Asymmetric Information, Screen Use Intensity, Screen Addiction, Impact on Productivity, and Mental Hygiene. This provides a broader analytical perspective than studies that rely exclusively on screen-time measures.

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Second, the study combines Exploratory Factor Analysis (EFA) and Partial Least Squares Structural Equation Modelling (PLS-SEM) to examine both measurement quality and structural relationships. The integrated use of these techniques strengthens the reliability and validity of the findings.

Third, the research incorporates both mediation and moderation analysis within a single framework. This enables the identification of underlying behavioural mechanisms as well as the conditional influence of informational asymmetries on digital engagement.

Finally, the study operationalises Screen Use Intensity and Screen Addiction as distinct constructs. This distinction provides a more refined methodological approach for analysing digital behaviour and helps avoid treating all forms of digital engagement as conceptually equivalent.

5.6.3 Empirical Contributions

The study makes several empirical contributions to the literature.

First, it provides empirical evidence regarding the behavioural consequences of Digital Access and Asymmetric Information using data collected from Indian respondents. Given the limited availability of empirical evidence on the attention economy in the Indian context, the study contributes to an underexplored area of research.

Second, the findings demonstrate that both Digital Access and Asymmetric Information significantly influence Screen Use Intensity and Screen Addiction, thereby identifying two important determinants of digital behavioural outcomes.

Third, the study provides empirical evidence that Screen Addiction, rather than Screen Use Intensity, constitutes the principal mechanism associated with productivity-related consequences. This finding challenges the widespread assumption that screen time alone is an adequate indicator of digital harm.

Fourth, the mediation analysis identifies Screen Addiction as a significant transmission mechanism linking Digital Access and Asymmetric Information to productivity outcomes, while the moderation analysis demonstrates that informational asymmetry conditions the relationship between Digital Access and Screen Use Intensity.

Overall, the study contributes new evidence on the behavioural pathways through which digital market conditions influence individual outcomes. In doing so, it provides a foundation for future research examining the economic, behavioural, and regulatory dimensions of the attention economy.

5.7 Limitations of the Study

Despite its contributions, the present study is subject to certain limitations that should be considered when interpreting the findings.

First, the study employed a cross-sectional research design, which limits the ability to establish temporal ordering and definitive causal relationships among the constructs. Although the hypothesised relationships were grounded in established theoretical frameworks, longitudinal evidence would provide stronger support for causal inferences.

Second, the analysis relied on self-reported questionnaire data. Such measures may be affected by recall bias, social desirability bias, and subjective interpretation, particularly when assessing behavioural constructs such as screen addiction, productivity, and mental well-being.

Third, the study measured digital engagement using perceptual indicators rather than objective behavioural data. Actual screen-time records, platform usage logs, and digital activity analytics may provide more precise measures of engagement and behavioural dependency.

Fourth, while the model demonstrated satisfactory explanatory power for productivity-related outcomes, the explanatory power for Mental Hygiene was comparatively limited. This suggests that psychological well-being is influenced by additional social, environmental, and personal factors that were beyond the scope of the present framework.

Finally, the study primarily examined the user-side consequences of the attention economy. Platform-side factors such as algorithmic design, recommendation systems, engagement-maximisation strategies, and advertising architectures were not directly analysed. Consequently, the findings provide only a partial view of the broader dynamics underlying attention-based digital markets.

Notwithstanding these limitations, the study provides a robust empirical framework for examining the behavioural pathways through which digital market conditions influence individual outcomes and offers a foundation for future research in this area.

5.8 Recommendations for Future Research

The findings of the present study suggest several directions for future research.

First, future studies may employ longitudinal or panel-data designs to examine how digital engagement behaviours evolve over time and to provide stronger evidence regarding causal relationships among the constructs.

Second, researchers may incorporate objective behavioural indicators such as screen-time records, application usage logs, browsing histories, and digital activity tracking data. Combining survey-based measures with behavioural data would improve measurement accuracy and reduce reliance on self-reported responses.

Third, future research may utilise multi-group analysis to investigate whether the relationships identified in this study vary across demographic groups, occupational categories, age cohorts, or lev-

els of digital engagement. Such analysis would provide a deeper understanding of heterogeneity in behavioural responses.

Fourth, greater attention should be devoted to the supply-side dynamics of the attention economy. Future studies may examine how platform business models, algorithmic recommendation systems, targeted advertising, data monetisation practices, and engagement-optimisation strategies contribute to attention capture and behavioural dependency.

Fifth, future research may explore additional outcome variables beyond productivity and mental well-being, including academic performance, decision quality, consumer welfare, social capital, labour market outcomes, and economic behaviour.

Finally, future studies may further investigate the market failure implications of attention-based digital markets by examining behavioural externalities, digital consumer protection, competition policy, algorithmic governance, and regulatory interventions. Such research would contribute to the development of more comprehensive economic frameworks for analysing digital markets in which attention functions as a scarce and strategically managed resource.

Taken together, these directions provide opportunities to extend the present research and deepen understanding of the behavioural and economic consequences of the attention economy.

5.9 Conclusion

This study set out to examine whether the attention economy generates conditions that may contribute to market failure through its influence on user behaviour. In an increasingly digitalised environment, where platforms compete for attention rather than merely providing information, understanding the behavioural and economic consequences of digital engagement has become an important area of inquiry. By integrating Attention Economy Theory, Information Asymmetry Theory, Behavioural Economics, and Market Failure Theory, the study developed and empirically tested a framework linking Digital Access, Asymmetric Information, Screen Use Intensity, Screen Addiction, Impact on Productivity, and Mental Hygiene.

The findings provide several important insights. First, both Digital Access and Asymmetric Information were found to significantly influence Screen Use Intensity and Screen Addiction, confirming that digital engagement is shaped not only by technological accessibility but also by the informational advantages possessed by digital platforms. The stronger influence of Asymmetric Information highlights the growing importance of platform intelligence, behavioural data, and algorithmic systems in directing user attention and shaping engagement patterns.

Second, one of the most important findings of the study is the distinction between Screen Use Intensity and Screen Addiction. While Screen Use Intensity did not significantly influence Productivity or Mental Hygiene, Screen Addiction emerged as a significant determinant of productivity-related outcomes and a key mediating mechanism within the model. This finding challenges the widespread assumption that screen time itself is inherently harmful. Instead, the results suggest that adverse outcomes arise primarily when digital engagement evolves into compulsive and dependency-oriented patterns of behaviour. The distinction between intensive use and problematic use therefore represents an important contribution to understanding the consequences of digital technologies.

Third, the mediation and moderation analyses provided deeper insight into the mechanisms operating within attention-based digital markets. The findings demonstrate that Screen Addiction serves as the principal pathway through which Digital Access and Asymmetric Information influence productivity outcomes. In contrast, Screen Use Intensity did not function as a significant mediator. The moderation analysis further revealed that informational asymmetry alters how access translates into engagement, indicating that platform-controlled informational advantages increasingly shape user behaviour. Together, these results suggest that behavioural outcomes in digital environments are influenced by the interaction of technological access, informational power, and behavioural responses.

From a broader economic perspective, the findings provide evidence that the attention economy exhibits several characteristics commonly associated with market failure. Informational asymmetries enable platforms to influence behaviour in ways that are not always fully transparent to users, while productivity-related costs associated with addictive engagement are borne primarily by individuals rather than by the platforms that benefit from prolonged attention. This divergence between private

incentives and broader welfare outcomes suggests that digital attention markets may not always generate socially optimal results. The study therefore supports the argument that attention has emerged as an economically valuable resource whose allocation carries important welfare implications.

Overall, the study demonstrates that the central concern within the attention economy is not digital participation itself, but the behavioural conditions under which participation occurs. Digital technologies provide substantial benefits in terms of information access, communication, learning, and connectivity. However, when platform incentives encourage dependency-oriented engagement, these benefits may be accompanied by productivity-related costs that are not fully reflected in market transactions. Consequently, understanding the economic implications of the attention economy requires moving beyond simple measures of screen exposure and focusing instead on the behavioural and informational mechanisms through which digital platforms shape attention.

The study contributes to the growing literature on digital markets by providing theoretical, methodological, and empirical evidence on the behavioural pathways linking platform environments to individual outcomes. More importantly, it highlights the need for future research, policy discussions, and regulatory frameworks that recognise attention as a scarce economic resource and address the challenges arising from its strategic capture and monetisation. As digital platforms continue to expand their role in economic and social life, ensuring that technological innovation remains aligned with individual welfare and broader societal objectives will remain a critical challenge for researchers, policymakers, and market institutions alike.

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