EXPLORING ASSOCIATIONS BETWEEN PROBLEMATIC INTERNET USAGE, SOCIAL MEDIA AND COMMUNICATION APPS USE UTILIZING EXPLORATORY GRAPH ANALYSIS

By

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NATIONAL UNIVERSITY OF MODERN LANGUAGES
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Candidate of **Master of Science in Computer Science (MSCS)** at the National University of Modern Languages do hereby declare that the thesiss "**Exploring Associations Between Problematic Internet Usage, Social Media, and Communication Apps Use utilizing Exploratory Graph Analysis"** submitted by me in partial fulfillment of MSCS degree, is my original work, and has not been submitted or published earlier. I also solemnly declare that it shall not, in future, be submitted by me for obtaining any other degree from this or any other university or institution. I also understand that if evidence of plagiarism is found in my thesis/dissertation at any stage, even after the award of a degree, the work may be cancelled and the degree revoked.

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ABSTRACT

Modern lifestyles have been profoundly impacted by the ubiquitous use of smartphone, which has raised concerns regarding the potential effects on well-being. Satisfaction with life (SWL) and Problematic Internet Use (PIU) have become vital constructs for understanding how excessive smartphone usage affects individuals. However, the relationship between PIU dimensions, SWL, and category-wise smartphone app usage remains inadequately explored, particularly when combining subjective assessments and objective app usage data. Recent studies have overlooked the relationships among PIU, SWL, and category-wise smartphone app usage while exploring the central roles of key variables and clustering patterns. A better knowledge of these relationships is required to address the issues raised by excessive smartphone use and its implications for well-being. Data from 269 individuals was gathered using a digital well-being app for this study, and exploratory graph analysis (EGA) was used to evaluate the data. The SWL Scale and the PIU Questionnaire Short-Form (PIUQ-SF-6) were filled out by participants. Their use of smartphones was tracked for few months aiming to capture the apps use patterns. The descriptive analysis, co-relations analysis, EGA were deployed to study the nature of data, relationships, and to uncover the association, centrality, and clustering between PIU, SWL, and category-wase smartphone apps usage. The study found strong relationships between PIU dimensions and SWL. Category-wise app usage, particularly social media and communication apps was strongly linked to negative PIU outcomes and lower SWL. Centrality analysis showed key variables driving the network, whilst clustering revealed different behavioral patterns associated with app usage and well-being. The findings emphasize the necessity of tailored interventions in reducing the negative impacts of excessive app usage and improving digital well-being. This study lays the framework for future studies and practical applications in promoting healthier digital behaviors by providing a more in-depth understanding of their dynamics.

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Nighat Perveen

DEDICATION

This thesis work is dedicated to my parents and my teachers throughout my education career who have not only loved me unconditionally but whose good examples have taught me to work hard for the things that I aspire to achieve.

CHAPTER 1

INTRODUCTION

Digital wellbeing refers to a person’s positive relationship with the usage of digital technologies and online activities to keep himself/herself healthy and to keep a balance in using digital technologies for a happier life. It also refers to the digital technologies' influence on the living of a good life in an information society [1]. The fast use of digital technologies has altered our interactions with ourselves, others, and nature. Our individual and social well-being is increasingly linked to our information environment and digital technologies. This raises ethical concerns about the impact of digital technologies on our well-being that must be addressed. [2]. Digital wellbeing is also concerned about the subjective well-being in a social environment [3], which is a self-valuation or declaration people make about the quality of their lives [4], [5], [6]. Happiness encompasses pleasure and fulfilment, including aspects like purpose, pleasant relationships, and social functioning. Subjective well-being measures often contain a cognitive appraisal, such as life satisfaction overall or in specific categories, as well as positive and negative affect [7]. Explanations for variations in happiness commonly involve health, work, and relationships [8], [9], [10]. Some think that digital technology will usher in a new era of enhanced productivity and help reduce social inequality by enabling improved access to currently restricted services, such as healthcare [11], [12].

Digital Health is a growing subject of research at the interface of healthcare and digital technologies that has received a lot of interest over the last decade around the world. In 2019, the American Medical Association reported that businesses have invested billions of dollars in innovative digital health entrepreneurship [13]. The US Food and Drug Administration evaluates a wide range of technologies, including digital health, mobile health, wearable devices, telehealth and telemedicine, health information technology, and personalized medicine [14]. WHO underlines that digital health can be advantageous to reaching the Sustainable Development Goals by making health and wellness services accessible with high standards for all people worldwide [15].

Artificial intelligence and machine learning have recently been used as vital methodologies in the digital health area, combining with Information and Communication Technology (ICT) and other technologies to tackle consumer and patient concerns [16]. Communication is essential for the delivery of health-care services since it connects the practitioner with the patients. Smartphone technology has recently provided the healthcare sector with a variety of communication channels [17].

With the rapid advancement of Internet technology, electronic devices such as smartphones have become one of the primary instruments for individuals to access and supply information. The popularity and recent fast developments in the usage of smartphones have changed the way people communicate and share information, also it has changed the users' interest and demands [18]. The influence of smartphones on different sectors has already been started, i.e., markets, corporations, society, and even individuals [19]. Researchers have started to investigate both the positive and negative effects of smartphones on service providers, their consumers, and effects on the whole of society [20]. During the COVID-19 lockdown, smartphones were the significant platforms for individuals from several sectors to work from their homes to keep the flow of their business responsibilities [21], [22]. Furthermore, the students also took advantage of using smartphones having internet facilities to keep progress in their educational and professional careers [21]. Similarly, the use of smartphones benefitted the young generation by enhancing their social skills and keeping their distance from the face-to-face interactions associated with peer influences, stress, and anxiety [23], [24]. The usage of smartphones, on the other hand, have also negative effects on the well-being of the users. Low self-esteem, poor daily work performance, mood disorders, and poor sleep quality are several psychiatric and personality issues linked to the excessive usage of smartphones [25].

An increasing body of research has investigated the possible consequences of Problematic Internet Use (PIU) to mental health and SWL. The rising amount of time people spend using smartphones, the range of activities people may do on them, and the resultant psychological relevance it assumes in people's life have motivated researchers to examine the influence it may have on users' mental health and well-being [26]. Technology addiction is characterized as "non-chemical, behavioral addictions that involve human-machine interactions" [27]. The World Health Organization's ICD-11 now officially recognizes Gaming Disorder, which includes both online and offline gaming [28]. Smartphone addiction is described as the excessive use of smartphones to the point where it interferes with the users' daily life priorities.

Current app designs, particularly those for smartphones and social media, promote addictive behaviors[29]. Given the significant overlap between problematic social media use and Problematic Internet Use (PIU), high scores on PIU measures may indicate problematic use of communication-based apps [30]. This raises the question: are certain platforms associated with higher levels of PIU? Prior research such as [31] has partially addressed this, indicating a strong positive correlation between PIU and problematic use of WhatsApp and Facebook. However, this examination was limited to bivariate correlations using subjective smartphone usage data.

Motivated by existing literature, this study aims to explore the associations between Problematic Internet Use (PIU) dimensions, SWL items, and category-wise smartphone app usage, including social media and communication apps, using a network analytic framework to uncover item-level relationships, central roles, and clustering patterns.

1.1 Background Motivation

The concept of digital well-being has its roots in the early 2000s, as the proliferation of digital technologies, including smartphones, social media, and other online platforms, began to reshape human behavior and interactions. With the increasing integration of technology into daily life, researchers and policymakers started to explore its potential negative effects on mental health, physical well-being, and social connections.

Internet addiction and excessive screen time were linked to issues like reduced attention spans, poor sleep quality, and increased levels of anxiety and depression [32]. There were the early issues. In 2010s the utilization of smartphone and social media became the essential part of personal and professional life and thus such issues were more apparent. Resultantly, features like screen time control, app usage tracking were introduced by companies like Apple, Facebook, and Google aiming to encourage digital wellbeing [33]. Researchers started to study the psychological and behavioural impact of technology use, as for example, internet addiction, fear of missing out (FoMO), and the effects of social media on mental health [34]. The digital well-being domain has emerged as a multidisciplinary field, integrating insights from public health, psychology, and HCI. This development stresses the importance of designing morally sound and human-centered technologies that promote balanced usage while minimizing potential harm. The COVID-19 pandemic increased dependence on work from home, online education, business, and conversation. Recently, the integration of digital technologies has increased into almost every aspect of daily life making the need for digital well-being more vital in the modern era.

Researchers have stated that the overuse of digital platforms are associated to increase anxiety, stress, poor sleep quality, and physical health problems [35]. The importance of promoting healthy digital behaviours has been further emphasized by the widespread usage of social media and its correlation with problems including cyberbullying, social comparison, and FoMO [36]. The increasing use of social media and its association with issues like cyberbullying, FoMO, and social comparison have increased the importance of promoting healthy digital behaviors. To encourage conscious usage of technology, governments, organizations, and tech companies have begun to place a higher priority on digital well-being. Researchers are actively studying the complex relationship between technology use and mental, physical, and social health with to create evidence-based tactics for encouraging healthy digital behaviours. Excessive social media use, screen time, and digital addiction have been associated to stress, anxiety, and depression by researchers in their studies on the psychological effects of these behaviours [37]. Interdisciplinary approaches, knowledge from psychology, behavioural science, and HCI, have been adopted to find solutions that decrease these negative impacts of technology use [38].

1.1.1 Digital Wellbeing

On the rise of the use of digital technologies, the notion of digital wellbeing has become an impactful research domain. The aim of digital wellbeing is to promote a healthy, balanced relationship with technology to augment mental, physical, and emotional well-being. On the increasing use and the adoption of technology, understanding and researching that how recent technology use affects wellbeing is becoming central for people, companies, and society. This adoption of digital technologies give birth to the domain of “Digital Wellbeing” in the late 20th century, when personal computers, smartphone use, and the internet were rapidly becoming popular. Initially, concerns revolved around internet addiction, a term introduced in the mid-1990s, which highlighted compulsive online behaviors and their impact on mental health [39]. With the rise of smartphones in the early 2000s, the focus shifted to mobile technology's pervasive role in personal and professional lives. Researchers identified issues such as nomophobia (no-mobile-phone-phobia) and excessive screen time as contributors to stress and anxiety [40]. By the late 2010s, the term "digital wellbeing" gained traction as a holistic concept, emphasizing not just reducing harm but also optimizing the benefits of technology. In recent years, digital wellbeing has evolved into a multidisciplinary domain, intersecting psychology, computer science, and human-computer interaction. Major technology companies like Google and Apple incorporated digital wellbeing tools into their products, such as screen-time trackers and focus modes, reflecting a growing societal awareness.

This study investigates the ways in which these platforms affect mental health and self-esteem. Digital technology and sleep are another important topic. Studies have shown that extended screen usage, particularly before bed, interferes with sleep cycles and lowers the quality of sleep [41] . Significant insights into this link have been gained from objective examinations of smartphone usage, such as data on attention and sleep modes. Furthermore, mindful use and digital detoxes have drawn more attention, with apps and digital detoxes serving as therapies to help users reduce the negative impacts of excessive screen time. According to studies, these techniques increase brain clarity and productivity. Lastly, developing human-centered technology that supports digital wellness is the main goal of ethical technology design. This includes functions that encourage better technology use and decrease compulsive tendencies, like app usage limitations and non-intrusive alerts.

1.1.2 Smartphone Usage and its Impact

Smartphones have revolutionized the way individuals interact, communicate, and manage their daily lives, offering numerous benefits across various domains. A significant aspect of their utility lies in the diverse range of mobile applications that cater to communication, productivity, education, health, and entertainment. Communication apps like WhatsApp, Zoom, and Microsoft Teams facilitate instant messaging, video calls, and virtual meetings, making it easier to stay connected with friends, family, and colleagues regardless of physical distance [42]. These apps are indispensable for fostering personal and professional relationships, enabling remote work, and supporting collaboration across geographies.

Educational apps such as Coursera, Duolingo, and Khan Academy democratize learning by providing access to courses, tutorials, and learning resources to users worldwide [43]. Similarly, health and fitness apps like MyFitnessPal, Sleep Cycle, and Calm empower users to monitor their physical and mental health, promoting better lifestyle habits. By offering features such as calorie tracking, sleep pattern analysis, and guided meditation, these apps encourage healthier behaviours and well-being. Additionally, navigation apps like Google Maps and Waze simplify travel, while utility apps for banking, shopping, and task management enhance productivity and convenience in daily life.

Entertainment and gaming apps also play a vital role in stress relief and leisure. Platforms like Netflix, Spotify, and various gaming apps offer users a way to unwind, fostering social interactions through shared experiences and multiplayer options. These positive aspects highlight the significant role smartphones play in enhancing various facets of life, making them an essential tool for modern living.

Despite their numerous advantages, excessive and inappropriate smartphone use can lead to negative psychological, social, and physical consequences. Social media apps like Instagram, Facebook, and TikTok are often associated with fear of missing out

(FOMO), social comparison, and reduced self-esteem. These platforms, designed to maximize engagement, can foster compulsive usage patterns, negatively impacting mental health and diminishing face-to-face interactions [37]. Moreover, the continuous bombardment of notifications from communication apps can lead to notification fatigue, blurring the boundaries between work and personal life and increasing stress.

Gaming apps, while entertaining, can contribute to addiction, particularly among younger users, leading to excessive screen time, reduced physical activity, and social isolation. Similarly, dating apps such as Tinder and Bumble, though valuable for building connections, may cause decision fatigue and emotional distress, especially when overused or misused [44]. Other apps, including shopping platforms and video-streaming services, can lead to impulsive spending and binge-watching behaviors, resulting in financial strain, time mismanagement, and sedentary lifestyles.

One of the most significant consequences of problematic smartphone use is its impact on sleep quality. Prolonged use of social media and entertainment apps before bedtime exposes users to blue light, which suppresses melatonin production and delays sleep onset [45]. This not only reduces sleep duration but also negatively affects overall well-being. Furthermore, excessive dependence on smartphones can lead to cognitive overload, reducing attention spans and impairing productivity.

1.2 Problem Statement

Concerns over smartphone usage effects on mental health and wellbeing, especially in the context of PIU, have been raised by its growing use. PIU has been connected to a number of psychological consequences, such as decreased life satisfaction and poor SWL. It is typified by behaviors like obsession, neglect, and control disorder. The type and frequency of app use, such as social media, messaging, and gaming apps, also has a big impact on how people behave. Nevertheless, little is known about the intricate connections among PIU dimensions, SWL items, and category-wise app usage.

The aim of this study is to address such research issues by exploiting EGA to research and visualize the network of associations among these constructs. The findings of this study will provide valuable insights into the linked aspects that influence digital well-being. The main hypotheses of this research work are listed below:

1.2.1 Association Research Questions

- **RP1**: What is the nature of the association between dimensions of PIU (obsession, neglect, control disorder) and life satisfaction indicators?
- **RP2**: How are specific PIU dimensions related to SWL items, and do these relationships indicate negative psychological consequences?
- **RP3**: In what ways does category-wise smartphone app usage influence PIU dimensions?
- **RP4**: How are patterns of app usage (e.g., social media, gaming, entertainment) associated with SWL items, and do some categories have stronger positive or negative impacts than others?

1.2.2 Clustering Research Questions

- **RP5**: Can EGA reveal distinct clusters or communities formed by PIU dimensions, SWL items, and category-wise app usage, based on their interrelationships?

1.2.3 Centrality Research Questions

- **RP6**: Which variables (e.g., PIU components, SWL items, or app usage categories) demonstrate the highest centrality in the network, indicating strong influence over the system?
- **RP7**: Do any SWL items serve as key bridge nodes between PIU components and app usage categories, as evidenced by high betweenness or bridging centrality?

1.3 Research Aims and Objectives

This study aim is to investigate the relationships between SWL items, PIU dimensions and category-wise app usage by deploying EGA. The main aim and objectives of this work is listed below:

- To explore the relationships between category-wise app use, SWL items, and PIU dimensions.
- To explore the effect of category-wise app usage on PIU and SWL.
- To identify distinct clusters among PIU, SWL, and app usage categories using EGA.
- To determine the central variables within the network that play a pivotal role in mediating the relationships among PIU, SWL, and app usage.
- To evaluate the stability and significance of the network structure through bootstrapped EGA.
- To provide insights into the behavioral and psychological patterns associated with smartphone usage and its impact on life satisfaction.

1.4 Thesis Contributions

This study makes several significant contributions to the field of digital wellbeing and behavioral informatics. The major contribution of this study is listed below.

- This study introduces the use of Exploratory Graph Analysis as a novel analytical approach to examine the complex interrelations among smartphone app usage, PIU dimensions, and SWL. This method goes beyond traditional correlation or regression techniques by identifying hidden structures and network patterns among variables.

- This study offers a multidimensional understanding of digital behavior by analyzing category-wise app usage (e.g., social, communication, gaming) and their distinct roles in shaping PIU and life satisfaction.

- This search work validates the theoretical constructs of PIU (Obsession, Neglect, and Control Disorder) and confirms the unidimensional nature of the SWL scale, thereby supporting their psychometric reliability in the present context.

- Furthermore, by applying centrality analysis, the research identifies key variables, such as SWL_3 and Obsession, as the most central or influential in the network, highlighting their importance as potential targets for digital well-being interventions. These findings offer practical implications for mental health practitioners, educators, and policymakers by suggesting data-driven strategies such as personalized digital detox plans, screen time management, and awareness campaigns.

Overall, the study advances both methodological applications and theoretical understanding in the domain of digital behavior and well-being.

1.5 Dissertation Organization and Outlines: A Big Picture

PIU and excusive smartphone use have negative impacts on mental health and well-being. Exploring the connections and effects between PIU, SWL, and category-wise app usage is vital as smartphone use continues to reshape many aspects of our daily life. The relation between these viable is multidimensional and sophisticated analytical techniques are required that can reveal linkages and patterns in the data. In this context, we utilize EGA, a network analysis technique for determining and visualizing the relationship between various variables.

In this study, first step is "Data Collection". In this phase, PIU, SWL data are gathered through surveys and app usage patterns via smartphone usage logs. In the second phase, data are processed and organized into a cohesive dataset for analysis. Finaly, EGA analysis are performed to examine the network of relationships among PIU dimensions, SWL items, and category-wise app use.

Chapter 1: Introduction. This chapter provide background, the notion of digital wellbeing, and the impact of smartphone use on digital wellbeing. Then problem statement, research hypothesis, and aims and objective are stated.

Chapter 2: Literature Review. The chapter discuss recent research that investigated how smartphone and app use affect PIU and SWL. Related literature are then summarized in a tabular form while identifies research gaps in the literature.

Chapter 3: Methodology. This chapter describes our research design, methodology, and instruments, including PIU and SWL questionnaires and smartphone usage time series data. It shows that how the acquired data have been processed to extract different features required for this study and elaborate on EGA.

Chapter 4: Results and Discussion. This chapter presents descriptive analysis, correlation analysis, studying and presenting the assumption analysis, and then the deployment of the EGA for network analysis. After the results, the findings are discussed in detailed in the context of the literature.

Chapter 5: **Conclusion and Future Directions**. Summarizes the main conclusions of the study and their significance for comprehending the connections between PIU characteristics, SWL items, and category-wise app usage.

CHAPTER 2

LITERATURE REVIEW

The increasing use of smartphones has considerably changed how people interact with their environment, communicate, and information acquisition. Despite the positive utilization of these technologies, their increasing use in daily life has also raised questions about problematic usage and its effects on well-being. This chapter presents related state-of-the-art research on PIU and smartphone addiction, emphasizing its behavioural, psychological, and societal aspects.

The proliferation of smartphones and applications, as well as their pervasive impact on modern lifestyles, are examined at the beginning of the chapter. It then explores the expanding body of studies on the detrimental effects of excessive usage, such as social dysfunction, psychological distress, and disruptions in one's academic or professional life. The conceptions of PIU and problematic smartphone use are at the center of this conversation, along with their relationships, underlying mechanisms, and important impacting factors, including personality traits, emotional regulation, and FoMO.

The chapter also presents results from recent studies using sophisticated techniques like network analysis, which reveal complex symptom structures and behavioral patterns, in order to provide readers a complete picture. This chapter presents the groundwork for comprehending the complexities of PSU and social media-related diseases by combining insights from several research streams. It also provides crucial background information for the studies that follow in this thesis.

2.1 Access to Information Communication Technology and Smartphone Adoption

In recent years, access to information and communication technology (ICT), such as smartphones, personal computers, and the internet, has expanded globally, radically altering social interactions, communication, and information access [46]. Among these, smartphones have emerged as the most ubiquitous and versatile ICT devices, offering far more than just basic functions like messaging and calling. Smartphones are often referred to as "minicomputers" because they integrate computing power into a portable form, allowing users to perform tasks traditionally reserved for desktop computers [47]. In addition to voice and text communication, smartphones support a wide array of functionalities, such as internet browsing, navigation, email, and access to social media platforms like Twitter, LinkedIn, and Facebook. These platforms, which are integral to modern digital communication, enable users to engage in virtual communities where they can share personal experiences, exchange knowledge, and receive social rewards like friendship, validation, and support [48]. This interaction within digital communities leads to crowd wisdom, where collective contributions enhance knowledge sharing, and in some cases, such as crowdfunding platforms, users receive financial support or contribute to collective creation. Smartphones are among the fastest-adopted technologies globally, and this widespread use has resulted in shifts in how individuals access information and manage daily tasks. The functionalities of smartphones go well beyond traditional communication, with individuals using them for entertainment (listening to music, watching videos), shopping, banking, and photography, which significantly alters the way people consume content and interact with their surroundings. This comprehensive integration of smartphones into daily life highlights their central role in shaping how individuals experience and engage with the world around them.

The widespread adoption of smartphones has, therefore, transformed not only the way people communicate but also how they consume information, engage in social interactions, and manage personal tasks. This shift has led to profound changes in both personal habits and societal norms, making smartphones central to both individual and collective experiences in the digital age.

2.2 Problematic Smartphone Use

While smartphone and social media use can improve one's daily life by providing access to information (for example, news and study materials), facilitating social connectedness, and providing additional entertainment options, there is growing concern about the potentially negative effects of excessive smartphone and social media use. This has prompted some researchers to begin looking into the possible addictive usage of these technologies [49]. Although these earlier works utilized addiction-terminology (e.g., smartphone addiction, social media addiction), scholars have moved away from this approach, hoping to avoid over-pathologizing behaviours that may be the new normal [50] [51]. It has also been stated that not all persons who are big digital technology users end up having problems in their lives because of that activity [52][53] [54] [55] [56] [57] [58] [59] to name a few1. In essence, most works have operationalized this phenomenon - in whatever way they term it - as challenges and interruptions in regular life caused by excessive smartphone/social media use [53]. As a result, although time-consuming use of digital technology is one side of the story, the other is the degree of disruption it causes in people's lives [60].

To reduce fragmentation in this research field and to seek for improved clarity, researchers have specifically advocated to employ the problematic digital technology (e.g., smartphone) [61] or digital technology (e.g., smartphone) use disorder [58] However, each term has its own limitations. For example, the "problematic use" approach is ambiguous if it represents a person progressing from a "healthy" state to experiencing full-blown psychopathology or if it is the result [62]. However, the "use disorder" approach may also be problematic, as neither smartphone nor inappropriate social media use are recognized as illnesses in popular diagnosis guides. It is crucial to note that, at the time of writing, the discussion about nomenclature (as well as these constructions) was still ongoing.

Recent research have consistently established that PIU and problematic social media use are connected with feelings of sadness and anxiety.[63], [64], as well as other important factors, such as poorer academic achievement [65], decreased productivity, and riskier driving [66]. In addition, PIU has been associated with transdiagnostic constructs relevant to the development and maintenance of anxiety and mood disorders, such as emotion dysregulation [67], intolerance of uncertainty [68], excessive reassurance-seeking [69], personality traits, such as neuroticism [70], and fear of missing out [71]. Similarly to PIU, studies have found problematic social networks use to be associated both with psychopathology [72], transdiagnostic factors, such as fear of missing out and neuroticism [73], and decreased work productivity [74].

2.3 State-of-the-art literature

In recent years, the impact of social media and smartphone use on mental health has become an increasingly prominent research area, with numerous studies exploring the various factors that contribute to PIU, smartphone addiction, and social media-related disorders.

Brian et al. [64] investigated the associations between the use of different types of social media platforms and signs of depression and anxiety among young adults in the United States. They found that individuals using 7–11 social media platforms had significantly higher odds of increased depression and anxiety symptoms compared to those using 0–2 platforms, even after controlling for overall time spent on social media.

Schivinski [75] explored predictors of problematic social media use across various platforms, involving 584 participants. They found that 6.68% (39 participants) were potentially problematic users. Significant predictors of problematic social media use included intrapersonal motive, negative effects, daily social media use, surveillance motive, and positive affect, explaining 37% of the variance in problematic social media use. Intrapersonal motive was the strongest predictor. These findings contribute to the understanding of problematic social media use by emphasizing the importance of specific motives and emotional factors, aligning with existing research and offering insights for future studies and interventions.

Further, research has also focused on the intersection of smartphone use and social media addiction. A study by Chemnad et al. [76] examined the relationship between social media app usage on smartphones and PIU among 334 participants interested in monitoring and regulating their smartphone usage. The four different usage clusters were found by the study through the analysis of app usage data from a smartphone application: the Light SM Use Cluster, the Conversational SM Cluster, the Highly Visual SM Cluster, and the Social Networking Cluster. Every cluster showed distinct app usage trends and matched PIU scores. These results show that different forms of social media use have varying implications for problematic usage and addiction risk, highlighting the complexity of social media use patterns and their varied correlations with PIU, In another study,

Another study Sariyska et al. [31] Another study examined the connection between excessive usage of social media sites like Facebook and WhatsApp and Smartphone usage Disorder (SUD), considering the roles of FoMO and life satisfaction. 2299 individuals' data indicate a correlation between SUD and WhatsApp Use Disorder, especially in women. FoMO modulates the association between life happiness and social media use disorders and predicts SUD. The findings highlight the importance of understanding WhatsApp use in relation to SUD and shed light on the mediating role of FoMO in social media-related disorders and life satisfaction. The relationship between Fear of Missing Out (FoMO) and the impact of social media use on daily life and productivity at work, as well as the mediating role of Use Disorders on platforms like WhatsApp, Facebook, Instagram, and Snapchat were studies in [74]. Data from 748 German-speaking participants showed that all social network Use Disorders were positively correlated with FoMO and social media's negative impact on daily life and work productivity. Mediation analyses revealed that Snapchat Use Disorder did not mediate the association between FoMO and these negative impacts, contrasting with the other platforms. These findings emphasize the central role of FoMO in digital technology-related disorders.

Additionally, Rozgonjuk et al. [77] investigated specific social networking platforms and their relationship with problematic smartphone use among German-speaking adults, revealing that Facebook and Instagram usage patterns differed significantly from WhatsApp. The study found minimal cross-platform symptoms between problematic smartphone use and WhatsApp usage, with physical symptoms (such as wrist and neck pain) being the only significant overlap. This study suggests that distinct social media platforms are associated with unique patterns of usage behavior and that problematic use of some platforms may more closely resemble smartphone use disorders than others. These findings emphasize that different social media platforms engage users in unique ways, impacting their mental and physical health differently.

Gao et al. [78], using network analysis, investigates the connection between problematic mobile phone use (PMPU) and behavioral inhibition/activation systems (BIS/BAS). BIS/BAS and smartphone addiction assessments were used to evaluate 891 young adults in total. "Mood modification," "tolerance," and "withdrawal symptoms" were found to be important central elements of the BIS/BAS-PMPU network. Notable associations were discovered between BIS and "tolerance" or "mood modification," as well as between BAS-fun seeking and "conflict" or "mood modification." The results provide information for focused prevention by pointing to possible pathways by which people with high BIS or BAS may acquire PMPU.

Peterka-Bonetta et al. [79] through an analysis of 331 participants' usage of Twitter and Instagram, the study explores the connection between personality factors and tendencies toward Internet Use Disorder (IUD), Smartphone Use Disorder (SmUD), and Social Networks Use Disorder (SNUD). The findings reveal that active social media usage (e.g., number of posts) is negatively correlated with IUD/SmUD levels, while receiving more reactions (likes and comments) is positively associated with SmUD severity. The study challenges the notion that greater social media activity predicts higher SmUD, suggesting instead that certain types of social media use may be beneficial. Additionally, the study replicates previous findings that higher levels of Extraversion, Conscientiousness, and Agreeableness are linked to increased social media activity, indicating that not all social media use contributes to problematic tendencies.

Research focusing on adolescents has also revealed significant findings regarding social media use and psychological distress. The study of Fortunato et al. [80] aimed to identify patterns of smartphone or social media use among adolescents and examine the associated levels of psychological distress. In a survey of 340 adolescents (average age 15.61), participants provided data on smartphone usage, social media addiction, online social comparison, emotion dysregulation, and psychological distress. Latent class analysis identified three distinct groups, with Class 3 (19% of participants) exhibiting higher levels of social media addiction and distress. The study found that heavy use of social media apps was not always linked to the most impaired psychological profiles. While excessive mobile screen time can indicate problematic use, the relationship between social media usage and psychological well-being is complex and requires further research.

In addition to social media-related disorders, the comorbidity and transition between different types of addictive behaviors are crucial areas of investigation. The study of M. Prokofieva et al. [81] examine their similarities and the possibility of comorbidity or switching between addictions, this study looked into the relationships between the symptoms of ten distinct addictive behaviors. The study used network analysis to find connections between addictions and symptom clusters using data from 968 persons who filled out self-assessments on activities like alcohol, drugs, tobacco, online gambling, internet use, gaming, social media, shopping, and exercise. Strong relationships between a variety of addictive behaviors were found in the data, with gambling exhibiting the highest centrality, followed by internet use, gaming, and other activities.

Y. Li et al. [82] studies the association among Chinese adolescents' PSU, internet gaming disorder (IGD), psychological distress, purpose in life, and problematic social media use (PSU). This work utilized network analysis on a dataset of 742 teenagers and stated that the main symptoms were withdrawal in IGD, mood modification in PSU, and tolerance in PSMU, while the bridge symptoms were withdrawal in PSMU and mood modification in IGD and PSU. It was discovered that stress is a major contributing component and that IGD, PSU, and PSMU are strongly associated with depression and meaning-related problems.

Liu et al. [83] have utilized network analysis and investigated the connection between the Big Five personality traits and signs of PSU. They considered 1,849 Chinese university students in this study, investigated the relationships between each personality trait and PSU symptoms as well as the bridging effects of these traits on the cluster of PSU symptoms. The findings show several patterns, including extraversion to escapism/avoidance, neuroticism to preoccupation, and neuroticism to escapism/avoidance. Conscientiousness has the most negative bridge centrality and neuroticism the highest positive bridge centrality, underscoring the nuanced ways in which personality qualities affect PSU.

Zhang et al. [84] investigates the unique network features of IGD and PSU in 7,246 teenagers. According to network research, the groups' network architectures differ significantly; for PSU, the primary symptoms are "feeling down, depressed, or hopeless," but for IGD, they are "feeling tired or having little energy." The results show that whereas SMA and IGD are both types of internet addiction, their psychopathological mechanisms are different. This suggests the need for tailored interventions targeting specific symptoms associated with each disorder.

Huang et al. [85] investigated the core symptoms of PSU in a large sample of grade 4 and grade 8 students, utilizing network analysis. The study uses the Smartphone Addiction Proneness Scale (SAPS) to analyze data from 11,687 grade 8 kids and 26,950 grade 4 students. They found that "loss of control" and "continued excessive use" are the main symptoms of PSU in both groups. Network analysis provides a fresh perspective on PSU and its symptom pattern, bolstering the argument for specialized treatments to target these fundamental symptoms. Similarly, [86] explored the relationship between problematic smartphone use (PSU) and symptoms of anxiety and depression, aiming to uncover the underlying pathological mechanisms. Making use of a network The study found significant relationships between PSU components and feelings of anxiety and depression based on data from 325 healthy Chinese college students. With the highest associations with symptoms of anxiety ("Restlessness") and sadness ("Concentration difficulties"), the "Withdrawal" component emerged as a major node. In both networks, "Withdrawal" also had the highest Bridge Expected Influence (BEI). The results point to PSU as a possible target for intervention and prevention since they imply that "Withdrawal" is a key factor in connecting it to anxiety and depression.

Qiu et al. [87] investigated the relationships between effortful control, mind wandering, and mobile phone addiction, focusing on dimension-level connections. The study, which included 1,684 participants, measured mind wandering, effort control, and mobile phone addiction using self-report scales. Network analysis was then used to assess the relationships between these factors. The findings showed clear and intricate correlations, with "spontaneous thinking" displaying the highest positive Bridge Expected Influence (BEI) and "activation control" having the highest negative BEI. The results offer insights into possible therapeutic targets by indicating that various aspects of effortful control and mind wandering have a significant impact on cell phone addiction.

Understanding the mechanisms and links behind problematic smartphone use (PSU) and how it relates to other behaviors and psychological factors has advanced significantly in recent years. [88] study investigates the mutual relationships between non-suicidal self-injurious (NSSI) behavior, PSU, and self-control, internalizing, and externalizing problems in adolescents. Through network analysis on data from 155 Italian adolescents, the study reveals that both NSSI and PSU may serve as attempts at emotion regulation, with low self-control and internalizing issues at the core of NSSI behavior. Notably, NSSI and PSU are interconnected via low self-control, and the study also observes that NSSI tends to decrease as adolescents age, though no gender differences are found. These findings suggest a need for prevention strategies that focus on enhancing self-control and healthy emotion regulation to mitigate risk behaviors during adolescence.

Tateno et la. [89] further examines PSU by analyzing the symptom network structure of PSU using the Smartphone Addiction Scale-Short Version among 487 college and university students. Employing network analysis, Khan identifies withdrawal and preoccupation symptoms as central components within the PSU symptom network, as indicated by their high centrality scores. These results imply that withdrawal and preoccupation are pivotal to the persistence and development of PSU. This study supports findings from previous research on school-aged children and highlights the value of longitudinal studies to track how these central symptoms influence PSU over time.

Expanding the investigation to specific social networking platforms, [90] study explores the associations between PSU and problematic usage of platforms like Facebook, WhatsApp, and Instagram in a sample of 949 German-speaking adults. Through bivariate correlation and exploratory graph analysis (EGA), the study uncovers distinct patterns: while problematic Facebook and Instagram use appear as separate behaviors, problematic smartphone and WhatsApp use are closely linked, possibly indicating shared constructs. A unique cross-platform symptom identified is physical discomfort, such as wrist and neck pain, resulting from prolonged digital technology use. The stability of the EGA models strengthens the argument that while Facebook and Instagram usage behaviors might differ, PSU and WhatsApp use may be measuring related behavioral constructs.

2.4 Research Gap

Despite the growing body of literature on PIU and its impact on subjective well-being (SWL), there is a lack of studies that integrate objective smartphone usage data with self-reported measures of PIU and SWL. Most existing research relies heavily on subjective assessments, neglecting the granularity and accuracy offered by objective data, such as category-wise app usage patterns. Additionally, the complex interrelationships among PIU dimensions, SWL items, and different categories of smartphone use (e.g., social media, communication, gaming) remain underexplored. There is also limited application of advanced analytical methods, such as Exploratory Graph Analysis (EGA), to uncover hidden patterns and network structures within this data. This gap underscores the need for a comprehensive approach that combines objective and subjective data to provide deeper insights into the behavioral and psychological impacts of smartphone use.

Table 2.1: Summary of the related Literature.

Ref	Scales	Smartphone Use		Category-wise Apps Use		Methodology / Analysis	Description
		SR	Obj.	SR	Obj.		
[64]	-Patient-Reported Outcomes Measurement Information System - Epidemiological Studies - Depression Scale Patient -Health Questionnaire -Use of multiple social media platforms	✓	✕	✕	✕	Regression Analysis	Examines the relationship between multiple social media platform use and depression/anxiety symptoms in young adults.
[31]	-Smartphone use disorder -WhatsApp use disorder -Facebook use disorder -Life Satisfaction -FoMO	✓	*X*	✓	✕	Regression and Mediation analyses	Investigates the link between Smartphone Use Disorder and excessive use of WhatsApp & Facebook, considering life satisfaction & FoMO.
[76]	-PIU -Social media app average use	✓	✕	✕	✕	Cluster Analysis	Examines the relationship between social media app usage and PIU.
[60]	-Disorder Scale (d-KV-SSS -Fear of Missing Out (FoMO) scale -WAUD, FBUD, IGUD, SCUD, and FoMO scales	✓	*X*	*X*	*X*	mediation analyses, correlation analyses, independent t-tests	Explores the impact of Fear of Missing Out (FoMO) on productivity and daily life linked to social media use.
[91]	Smartphone Addiction Scale PWU, PFU, and PIU scale	✓	*X*	*X*	*X*	-EGA psychometric scales (PSU, PWU, PFU, PIU) Gaussian Graphical Model (GGM) EBIC GELASSO.	Investigates associations between problematic smartphone use and specific social networking platforms.
[88]	-Internet Gaming Disorder Scale-Short Form -Smartphone Application--Based Addiction Scale -Bergen Social Media Addiction Scale -Extended Meaning in Life Questionnaire -Depression, Anxiety, and Stress Scale	✓	*X*	*X*	*X*	Network analysis to examine interconnections between disorders.	Analyzes the relationship between internet gaming disorder, smartphone use, social media use, and psychological distress among adolescents.
[83]	-Problematic Smartphone Use Scale PSUS -Chinese Big Five Personality Inventory-15 (CBF-PI-15	✓	*X*	*X*	*X*	Network analysis examining Big Five personality traits and smartphone use.	Explores how personality traits influence problematic smartphone use using network analysis.
[84]	-Internet Gaming Disorder Scale-Short Form (IGDS9-SF) -Bergen Social Media Addiction Scale (BSMAS) -Patient Health Questionnaire-9 (PHQ-9)	✓	*X*	*X*	*X*	Network analysis to explore psychological and sleep symptoms of social media addiction and internet gaming disorder	Examines symptom differences between social media addiction and internet gaming disorder in Chinese adolescents.

	-Generalized Anxiety Disorder 7-item (GAD-7) -Pittsburgh Sleep Quality Index (PSQI)						
[85]	-Smartphone Addiction Proneness Scale (SAPS) -PSU scale	✓	X	X	X	Network analysis to identify core symptoms of problematic smartphone use.	Identifies core symptoms of problematic smartphone use in a large sample of students.
[86]	-Smartphone Application-Based Addiction Scale (SABAS)	✓	X	X	X	Network analysis of smartphone use and its relationship to anxiety and depression.	Investigates the link between problematic smartphone use and mental health symptoms in Chinese college students.
[87]	-Mobile Phone Addiction Tendency Scale (MPATS) -Effortful Control Questionnaire -Mind Wandering Questionnaire	✓	X	X	X	Network analysis on effortful control, mind wandering, and mobile phone addiction.	Explores how effortful control and mind wandering relate to mobile phone addiction.
[88]	-Brief Self-Control Questionnaire (BSCS) -Strength and Difficulties Questionnaire (SDQ) -Smartphone Addiction Inventory-Italian Version (SPAI) -Self-Injurious Thought and behavior Questionnaire-Nonsuicidal (SITBQ-NS)	✓	X	X	X	Network analysis to explore the relationship between self-harming behaviors and smartphone addiction.	Investigates the role of self-control and behavioral issues in self-harming adolescents with problematic smartphone use.
[89]	Smartphone addiction scale–short version	✓	X	X	X	Network analysis of problematic smartphone use in young adults.	Examines the central symptoms and factors contributing to problematic smartphone use among young adults.

CHAPTER 3

METHODOLOGY

In this chapter, we describe the methodology used to examine the relationship between PIU dimensions, SWL items, and category-wise smartphone usage. To study the relationships between the variables, descriptive statistics and correlation analyses have been performed followed by EGA. EGA is useful to find the relationship in a complex network of variable and for clusters detection and network structures in data.

An initial sample of **602** participants, from October 2020 to April 2021, in the study provided subjective PIU and SWL, and objective smartphone app usage data. Around 5.4 million raw app usage time series records were collected. The acquired apps use data was processed to extract significant features, i.e., category-wise app usage, and total smartphone use. After processing, a total of 269 participants were qualified for this study. This chapter further explore the different types of analysis that were performed on the PAS-Dataset.

3.1 Proposed Methodology

An abstract view of this study is given in Figure 3.1. Smartphone apps usage data was acquired via a dedicated smartphone app with an emphasis on digital well-being. A complimentary upgrade to the premium edition of the Digital Wellbeing app was given to participants who finished the PIUQ-SF-6 (Problematic Internet Use Questionnaire Short-Form) and SWL (Satisfaction with Life) surveys. During the survey, the participants also provided information, such as age, gender, and educational attainment, in addition to the smartphone usage data. Because the PIUQ-SF-6 and SWL questionnaires were written in simple English, individuals who were already familiar with smartphones and smartphone apps could easily complete it. It was assumed that participants would be sufficiently fluent in English because the Digital Wellbeing app was only available in that language. Participants gave their full permission after receiving complete details about the data collecting procedure and being made aware that their information would be kept anonymous and used only for research.

The data collected through the app included the PIU and SWL scores, as well as smartphone usage patterns. In this study, we introduced the concept of 'e-sleep,' which refers to periods of smartphone inactivity during designated sleeping hours. While e-sleep serves as a proxy for sleep patterns, it is acknowledged that individuals may still be awake but not using their smartphones during these times. The e-sleep dataset was compiled to investigate the relationship between smartphone usage and sleep quality, particularly focusing on the effects of smartphone abstinence during sleep and its impact on sleep quality. This data will be central to analyzing the role of smartphone usage in shaping well-being and digital habits.

The abstract view of this study is illustrated in Figure 3.1, providing an overview of the methodological framework used to investigate the relationships among PIU dimensions, SWL items, and category-wise smartphone app usage. Installing a specific smartphone app that recorded their usage activities, and the amount of time spent on different apps like social media, communication, and gaming was mandatory for participants. Explicit consent was taken that the data of this study will be used for research purpose anonymously. The app started gathering information on participants' smartphone use, such as the amount of time spent on various app categories, after the initial questions were finished. This data provided a solid foundation for research and served as the basis for the study's dataset, known as the PAS-Dataset, which included 269 participants. Furthermore, the R language was utilized for analysis. The results were compiled and variable associations were investigated using descriptive statistics, correlation, and EGA analysis.

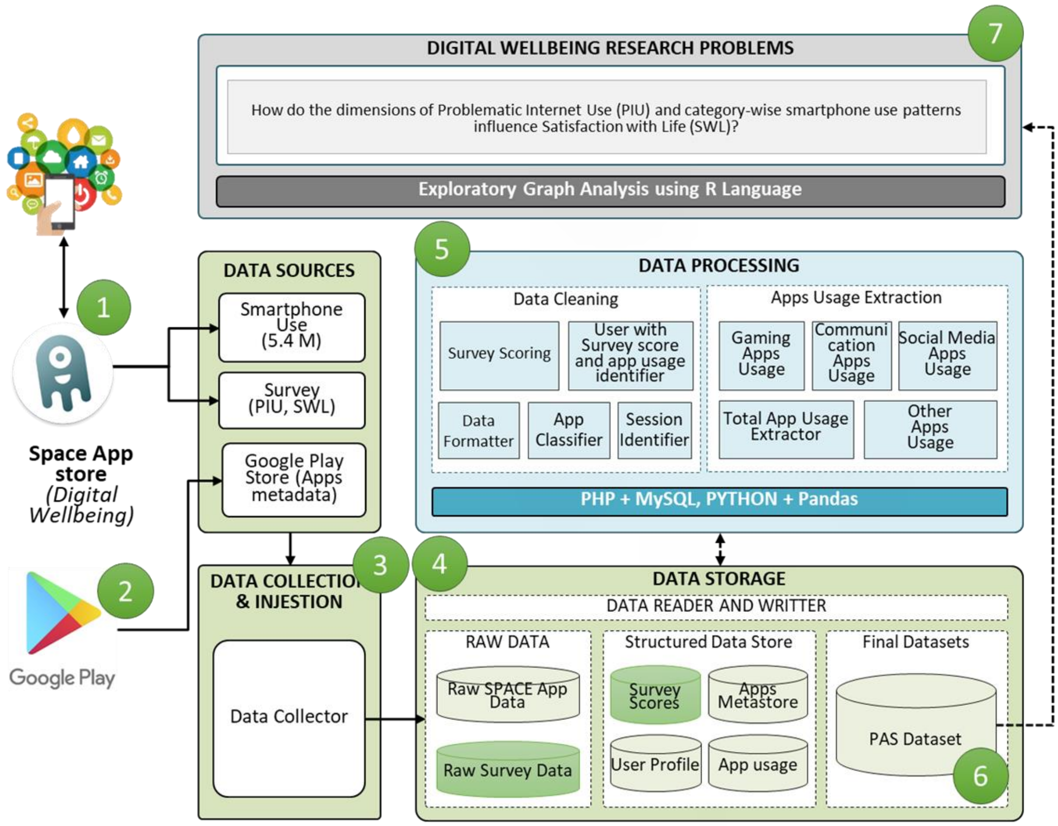

Figure 3.1: An abstract view of the proposed methodology.

3.2 Measures

3.2.1 Data Acquisition and Processing

This study, conducted from October 2020 to April 2021, 602 participants participated who provided informed consent, setting the stage for a thorough investigation. The dataset consisted of approximately 5.4 million app usage records, offering a comprehensive and extensive collection of data for analysis. At various times, participants downloaded the app and signed up for our research. We considered their first week of use in this study. To accurately represent a normal usage behavior, previous studies found that at least five days are needed [92], [93]. We took into consideration that weekends are part of the seven days and mitigate their impact. Participants were excluded from the analysis if they failed to meet the following criteria: (i) a minimum of seven consecutive nights with complete app usage data; or (ii) a minimum of 16 hours of recorded app usage within a 24-hour period, which is the maximum feasible duration for a day. This filtering process was applied to eliminate participants who had poor sleep-wake cycles. The latter was created to omit situations in which data synchronization failed, such as when the internet was unavailable for an extended period. After applying the filtering criteria, a total of 269 participants' data were deemed suitable for analysis.

Figure 3.1. provides a visual representation of app usage patterns, where 'Start Time' and 'End Time' denote the beginning and end of each app usage session, respectively, and 'App Name' indicates the specific smartphone app being used during that session. The terms "User Code" and "App Name" denote the user, the smartphone app being used, and the unique code "Sequence ID" that represents the user's usage activities.

<table>
<tr><th>Sequence ID</th><th>User Code</th><th>App Name</th><th>Start Time</th><th>End Time</th></tr>
<tr><td>757</td><td>etfgc{td|83>6As``ge/nml</td><td>Maps</td><td>23-Sep, 0:14:53</td><td>23-Sep, 0:14:55</td></tr>
<tr><td>758</td><td>etfgc{td|83>6As``ge/nml</td><td>Spotify</td><td>23-Sep, 0:14:55</td><td>23-Sep, 0:15:33</td></tr>
<tr><td>759</td><td>etfgc{td|83>6As``ge/nml</td><td>Spotify</td><td>23-Sep, 0:39:46</td><td>23-Sep, 0:39:49</td></tr>
<tr><td>760</td><td>etfgc{td|83>6As``ge/nml</td><td>Messenger</td><td>23-Sep, 0:39:50</td><td>23-Sep, 0:40:10</td></tr>
<tr><td>761</td><td>etfgc{td|83>6As``ge/nml</td><td>Chrome</td><td>23-Sep, 0:40:12</td><td>23-Sep, 0:44:02</td></tr>
<tr><td>762</td><td>etfgc{td|83>6As``ge/nml</td><td>Messenger</td><td>23-Sep, 0:44:05</td><td>23-Sep, 0:44:45</td></tr>
</table>

Figure 3.2: Apps use by participants.

Survey Scoring: In this operation, the participants’ raw PIU scoring data for each questionnaire were extracted and stored in a well-defined form back in survey scores storage.

Data Formatting: As the data has been collected from the participants belonging to different origins with their national languages, we performed language unification by merging different languages into a unified language i.e., English**.** Besides language unification, date and time are also formatted.

Apps Classification: Smartphone users install different types of apps and use them daily according to their priorities. We have performed apps classification operations to classify apps based on categories provided by the Google Apps Play Store.

Session Identification & Refinement: In this operation, the session of apps usage is identified for each user by the app usage start and end time. Those sessions that were created and closed in very little time are discarded except the sessions that are given proper time duration.

Identification of Users with Proper Surveys & App Usage: The participants for this study were selected based on their completion of the required surveys after installing the Space App, which tracked their smartphone usage. Only those who fully completed the surveys were included in the analysis, while those who did not meet this criterion were excluded. Additionally, participants who used the app for fewer than seven full days were excluded, as this insufficient data could not provide reliable insights into usage patterns. From the collected smartphone usage data, two key metrics were extracted: total smartphone usage time and category-specific app usage. The app categories considered for analysis included communication (COM), social media (SOCIAL), gaming (GAME), dating (DATING), web browsing (BROWSER), business (BUSINESS), beauty (BEAUTY), utility tools (TOOLS), entertainment (ENTERTAINMENT), finance (FINANCE), music (MUSIC), sports (SPORTS), health and fitness (HEALTH_FIT), education (EDUCATION), video streaming (VIDEO), parenting (PARENTING), and lifestyle (LIFESTYLE).

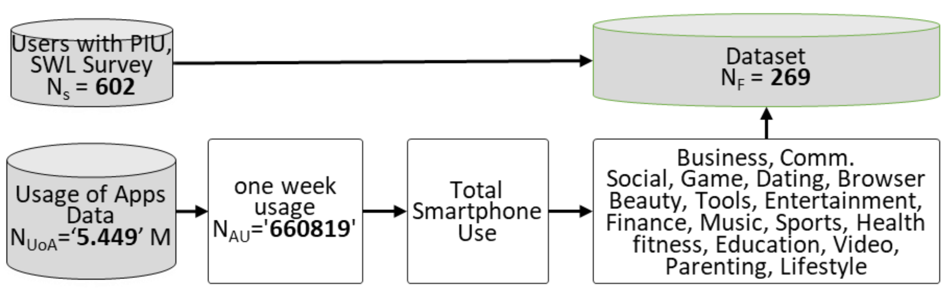

Figure 3.3: Flowchart showing the steps involved in gathering and processing the PAS Dataset.

3.2.2 Constructs

3.2.2.1 Problematic Internet Usage

Problematic Internet Usage refers to excessive and compulsive internet use that interferes with daily life, social relationships, and mental health [94]. To evaluate PIU, the PIUQ-SF-6 (Problematic Internet Use Questionnaire Short-Form 6) was employed [95]. The PIUQ-SF-6 is a condensed version of the original eighteen-item PIUQ-SF-6 scale, condensed into six items that assess smartphone addiction and problematic usage [96].

The PIUQ-SF-6 scale employs a 5-point Likert scale to evaluate the frequency of PIU behaviors, with responses ranging from 'never' (scored as 1) to 'always/almost always' (scored as 5). The scale yields a total score between 6 and 30, where higher scores signify a more severe level of PIU. This assessment tool enables researchers to quantify the extent of PIU and monitor changes over time, providing valuable insights into smartphone use habits and their potential impact on individuals. The measurements reported Cronbach's alpha is higher than 0.70 [95] and 0.82 [97], indicating acceptable validity.

PIU is comprised of three sub-variables: Obsession, Neglect, and Control-Disorder.

- Obsession refers to persistent, intrusive thoughts about being online, a constant urge to use the internet, and difficulty stopping even when trying to focus on other things, e.g., frequently thinking about checking apps or feeling anxious when not online.

- Neglect means ignoring personal, academic, or social responsibilities because of excessive internet or smartphone use, e.g., missing deadlines, skipping meals, or avoiding real-life social interactions due to time spent online.

- Control Disorder reflects the inability to regulate or limit internet use despite knowing it's causing problems in daily life, e.g., **t**rying to reduce screen time but failing repeatedly, leading to sleep issues or reduced productivity.

Each of these sub-variables is assessed by two questions in the PIUQ-SF-6 scale, which are rated on a 5-point Likert scale. Figure 3.7. shows the PIUQ-SF-6 questionnaire.

Table 3.1: Standardized factor loadings for the 6-item Problematic Internet Use Questionnaire Short Form (PIUQ-SF-6), illustrating the three-factor solution for each item [98].

		Obsession	Neglect	Control disorder
2.	How often do you feel tense, irritated, or stressed if you cannot use the Internet for as long as you want to?	0.82		
	How often does it happen to you that you feel depressed moody. or nervous when you are not on the Internet and these feelings stop once you are back online?	0.86		
1.	How often do you spend time online when you'd rather sleep?		0.54	
5.	How often do people in your life complain about spending too much time online?		0.72	
3.	How often does it happen to you that you wish to decrease the amount of time spent online but you do not succeed?			0.73
4.	How often do you try to conceal the amount of time spent online?			0.79
	Mean	1.53	2.10	1.55
	Standard deviation	0.77	0.87	0.76
	Obsession		.87	.80
	Neglect			.94
	Control disorder			

3.3 Satisfaction with Life Scale (SWLS)

SWLS is a key component of subjective well-being, reflecting an individual's overall cognitive evaluation of their life based on personal criteria (Diener et al., 1985). The scale consists of five statements that respondents rate based on their agreement, typically using a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). The responses are summed to provide a total score, with higher scores indicating greater life satisfaction. In literature, the SWLS has been shown to be valid and dependable across various cultures and populations, and is frequently used in research domain to measure overall well-being.

Table 3.2: SWLS Items.

SNO	Question	Strongly Disagreed	Disagree	Slightly Disagree	Neither Agree not	Slightly Agree	Agree	Strongly Agree
1	In most ways my life is close to my ideal.	1	2	3	4	5	6	7
2	The conditions of my life are excellent.	1	2	3	4	5	6	7
3	I am satisfied with my life.	1	2	3	4	5	6	7
4	So far, I have gotten the important things I want in life.	1	2	3	4	5	6	7
5	If I could live my life over, I would change almost nothing.	1	2	3	4	5	6	7

The description of all variables used in this study is provided in Table 1.

Table 3.3: Description of the research variables.

S#	Variable	Description
1	PIUQ-SF-6	PIUQ-SF-6 consists of three dimensions, i.e., Obsession, Neglect, and Control Disorder. It shows how internet use may affect social interactions, everyday life, and personal wellbeing, as elaborated in section 3.3.
2	SWL	The term "SWL" describes a person's overall evaluation of their level of life satisfaction as explained in section 3.4.
5	Average Smartphone Use	AvgSPUse is a continuous variable and provides information about how much time people spend on their smartphones on a daily average for a week.
7	Category-Wise Smartphone App Use	The classification of apps into distinct groups according to their main purpose is known as category-wise smartphone app usage, and it provides a deeper knowledge of how users interact with various app types. All these sub-variables are continuous and are listed below: • **Communication (COM)**: Apps used for messaging, calls, and email. • **Social media (SOCIAL)**: Platforms for social networking and sharing content.

- **Gaming (GAME)**: Apps designed for recreational and interactive games.
- **Dating (DATING)**: Apps for online dating and social interactions.
- **Web Browsing (BROWSER)**: Apps used for browsing the internet.
- **Entertainment (ENTERTAINMENT)**: Apps for streaming video, music, and other media.
- **Video Streaming (VIDEO)**: Apps for watching videos and streaming media.

3.4 Exploratory Graph Analysis

In this research, we use EGA [99] to investigate the dimensions of PIU, SWL items, and category-wise smartphone app usage. In this section, we elaborate on the EGA and use it for analysis with our research variables.

Estimating the correct number of dimensions remains a challenge in psychometrics, with various methods proposed, including parallel analysis (PA), Kaiser-Guttman's eigenvalue-greater-than-one rule, the multiple average partial procedure (MAP), and maximum-likelihood approaches that use fit indices like BIC and EBIC. In addition, the Very Simple Structure (VSS) approach, which is less well-known and explored, was evaluated. In this study, we use EGA, which is based on a graphical lasso and a regularization parameter set by EBIC.

Parallel analysis and the MAP have previously been demonstrated to perform effectively when there is a low or moderate correlation between factors, the sample size is equal to or larger than 500, and the factor loadings range from moderate to high [100]. However, they tend to underestimate the number of factors when the correlations between factors are high, the sample size is small, and there are few indicators per component [101].

The EGA approach is known as exploratory graph analysis (EGA) because it begins by generating a graphical model [102] and then uses cluster detection to estimate the number of dimensions in data**.** EGA has the added advantage over the preceding processes in that it estimates not only the number of dimensions, but also which items correspond to each dimension.

In EGA, variables are represented as nodes, and their relationships (often correlations or partial correlations) are depicted as edges in a graph. By applying algorithms like the Walktrap [103] or Louvain method [104], EGA partitions the graph into clusters or communities, which represent groups of closely related variables, suggesting the presence of latent factors. One key advantage of EGA over traditional methods like exploratory factor analysis (EFA) is its ability to capture complex, non-linear relationships and its reliance on data-driven, visual interpretations, making it an intuitive and flexible approach**.** EGA is increasingly applied in psychological measurement, psychometrics, and educational research to refine theoretical frameworks, develop instruments, or validate constructs. Its integration with software tools such as R (e.g., EGAnet package) has further enhanced its accessibility and applicability for researchers.

3.4.1 EGA Estimators

In the context of EGA, several estimators can be used to construct networks that reveal the underlying structure of the data. Below are the key estimators that can be utilized based on the nature of the data and research objectives:

1. **Correlation Networks**: This estimator is used to identify relationships between variables based on Pearson correlation. It’s suitable for continuous data where the goal is to understand linear dependencies between variables. However, it does not account for direct partial correlations and might be less effective in high-dimensional datasets.

2. **Partial Correlation Networks**: This approach allows for the estimation of direct relationships between variables by controlling for other variables in the dataset. It’s useful when you want to study conditional dependencies between variables, and it works well with continuous data, particularly when you need to filter out indirect relationships.

3. **EBICglasso Networks** [102] This method utilizes the graphical lasso technique combined with EBIC (Extended Bayesian Information Criterion) for regularization. It's particularly effective for sparse high-dimensional data, where the goal is to estimate

the precision matrix (inverse covariance) and select the most relevant connections. EBICglasso helps in choosing the optimal level of sparsity.

4. **Huge: High-dimensional Undirected Graph Estimation** [105] The Huge estimator is useful for handling high-dimensional datasets by estimating undirected graphical models. It is specifically designed to perform well with large datasets where the number of variables exceeds the number of observations. It provides an efficient way to identify structure in complex, high-dimensional data.

5. **Ising Network** [106] [107] These networks are tailored for binary or categorical data. The Ising model focuses on capturing pairwise dependencies in categorical data and is frequently used in social sciences and psychometrics to model interactions between binary variables, like presence/absence data or dichotomous response variables.

6. **MGM: Mixed Graphical Models** [108] The MGM estimator allows for the estimation of networks where variables can be of different types (e.g., continuous, ordinal, binary). It is particularly useful when dealing with mixed data types, which makes it ideal for your dataset that includes various types of variables like PIU dimensions, SWL items, and smartphone app usage categories.

The comparison of the EGA estimators is summarized in the following table.

Table 3.4: EGA estimators summary.

Estimator	Data Type	Pros	Cons	Recommendation
Correlation Networks	Continuous	Simple, fast	Ignores direct dependencies; does not capture conditional relationships	Not ideal for complex or high-dimensional data
Partial Correlation Networks	Continuous	Captures direct relationships, accounts for conditional dependencies	May struggle with high-dimensional data	Good for moderate-sized datasets with continuous variables
EBICglasso Networks	High-dimensional, Continuous	Regularized estimation, balances model complexity and fit	Requires careful selection of regularization parameter	Recommended for high-dimensional, sparse datasets

Huge (High-dimensional Undirected Graph Estimation)	High-dimensional	Designed for large-scale problems	Primarily for continuous data	Recommended for very high-dimensional data
Ising Networks	Categorical/Binary	Models pairwise dependencies in categorical data	Not suitable for continuous or mixed data types	Ideal for binary/categorical data or psychometric research
MGM (Mixed Graphical Models)	Mixed (Continuous, Ordinal, Binary)	Handles variety of data types, flexible	More complex to implement	Recommended datasets with mixed data types.

3.4.2 EGA Weights Matrix, Centrality, and Clustering

3.4.3 EGA Weights Matrix

The weights matrix shows the estimated relationships between variables in a matrix form, which is usually represented as a correlation/partial correlation. Larger value in the matrix shows stronger correlations between variables, which show the strength of the connection.

3.4.4 EGA Centrality

EGA Centrality refers to the measure of a node's influence within the network. It can be quantified using several centrality metrics, i.e., **Degree Centrality** (determines how many direct links there are between a variable and the network), **Closeness Centrality** (evaluates the speed at which a variable in the network may access other variables), and **Betweenness Centrality** (identifies variables that act as bridges between other variables)..

3.4.5 EGA Clustering

EGA Clustering groups variables into communities/clusters based on their relationships. This helps in identifying latent dimensions/factors in the data. Variables that are more strongly related will cluster together, reflecting shared patterns or characteristics. As for example, **Barrat** and **Onnela** focus on local clustering, while **WS** and **Zhang** give insight into the overall network structure and the strength of the community. Each measure can be useful depending on the context of the analysis and the type of data being analyzed.

Table 3.5: Comparison of Clustering Measures in EGA

Clustering Measure	Description	Purpose
Barrat Clustering	Based on the proportion of a node's neighbors that are connected to each other, evaluating local clustering.	Identifies how tightly interconnected a node's neighborhood is, indicating dense subgroups or communities.
Onnela Clustering	Focuses on the modularity of a network, assessing the strength of a node's community by considering its neighbors' connections.	Evaluates the robustness of community structures, showing how nodes form cohesive clusters based on shared traits.
WS (Watts-Strogatz) Clustering	Quantifies the clustering coefficient in small-world networks, comparing the density of triangles to the number of possible triangles.	Assesses the "small-world" properties of a network, providing insight into local node clustering within the overall structure.
Zhang Clustering	Evaluates the strength of community structures based on link prediction models, assessing the meaningfulness of connections.	Distinguishes strong community structures from weak or random connections, offering insights into the stability of clusters.

3.5 Summary

This chapter presented methodological approach for investigating the association between PIU dimensions, SWL, and category-wise smartphone app usage. The study uses a methodical strategy, starting from collection data and processing of data through app for digital well-being that monitors smartphone usage trends and gathers relevant information. To provide reliable and insightful investigations, vital factors such as PIU, SWL, and total smartphone use (TSU) are thoroughly evaluated and analysed. The study using of EGA and state-of-the-art technique for analysing and displaying complex correlations between variables. EGA enlighten the clustering, centrality, and association structure of the data. This makes it possible to find significant patterns and association between PIU dimensions, SWL, and category-wise app usage like social media, communication, gaming, and video streaming. This research hypothesis provides a thorough knowledge of the association between PIU and SWL by combining subjective evaluations of the two variables with objective smartphone usage statistics. The study aims to identify significant behavioural patterns and their possible effects on users' well-being using this methodology.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Sample Characteristics

The table provides specifics about the demographics of the sample, which consists of 269 people. Regarding the distribution of participants' genders, 41.03% of them identified as male (n = 103), but a higher percentage, 55.01%, identified as female (n = 148). The inclusion of diverse identities in the dataset is highlighted by the additional 6.69% (n = 18) who identified as belonging to other gender categories. With a notable acknowledgement of non-binary or alternative gender identities, this gender breakdown shows a balanced representation of men and women, enhancing the sample's diversity and deepening the demographic analysis.

The sample was divided into two main age groups: emerging adults (15–24 years old) and adults (25–64 years old). Adults totalled 55.13% (n = 145) of the sample, whereas emerging adults made up 44.86% (n = 118). This age grouping was selected to capture distinct life stages and related traits, offering significant insights into various points of view and experiences within different age groups. A little percentage of the data—2.23%, or n = 6—was categorized as missing, meaning that some respondents' age-related information was insufficient. Even though the amount of missing data is small, it emphasizes how important it is to report transparently and take potential gaps in demographic data into account.

Professionally, the participants were categorized into students and non-students, with students making up 34.94% (n = 94) and non-students representing a significant majority at 65.05% (n = 175). This distinction offers insights into the occupational status of the participants, which can have implications for their responses and perspectives within the broader scope of the study. The relatively high proportion of non-students suggests a diverse range of professional or occupational backgrounds, enriching the data with varied experiences and viewpoints.

Table 4.1: Descriptive Statistics for Demography.

Variables	Frequency (269)	Percent
Gender		
Male	103	41.03
Female	148	55.01
Others	18	6.69
Age		
Emerging Adults (15-24)	118	44.86
Adults (25-64)	145	55.13
Missing	6	2.23
Profession		
Students	94	34.94
Non-Students	175	65.05

4.2 Descriptive Statistics of category-wise app use variables

The descriptive statistics shown in Table **4.2**, indicate significant differences in smartphone app usage across gender, age, and profession. Females exhibit higher overall smartphone usage and significantly greater engagement with social media, while males show higher usage of gaming and web browsing apps. Emerging adults report the highest total mobile usage, particularly for communication and social media apps, compared to adults. Similarly, students display greater smartphone engagement, especially in social media and gaming, than non-students. These patterns highlight how demographic factors shape app usage behaviors, providing valuable insights for understanding and addressing problematic smartphone use.

Table 4.2: Descriptive Statistics of category-wise app use variables. Values with ± indicated the standard deviation. All the variables are continuous and are calculated in terms of the daily average in minutes.

	Male	Female	Students	Non-Students	Emerging Adults	Adults	Over all	Shapiro-Wilk	Shapiro-Wilk (Transformed)
Communication	37.856 (±39.818)	43.684 (±39.695	45.242 45.242	39.347 (±36.448	42.538 (±40.699	40.861 (±38.617	41.407 39.214	0.775	0.958

	Male	Female	Students	Non-Students	Emerging Adults	Adults	Over all	Shapiro-Wilk	Shapiro-Wilk (Transformed)
Social Media	46.946 (±56.014)	96.909 (±87.477)	83.464 83.464	73.505 (±77.331)	86.319 (±86.51)	70.623 (±75.498)	76.986 80.19	0.847	0.964
Gamming	13.92 (±26.221)	12.054 (±17.509)	16.086 (±16.086)	11.174 (±15.096)	14.865 (±27.234)	11.344 (±15.48)	12.89 21.475	0.59	0.882
Dating	3.163 (±12.746)	1.174 (±5.742)	3.154 (±3.154)	1.185 (±6.036)	2.642 (±11.476)	1.325 (±6.549)	1.873 9.002	0.216	0.304
Browser	44.133 (±58.599)	34.471 (±38.176)	35.73 (±35.73)	38.731 (±47.539)	34.99 (±43.108)	40.52 (±49.809)	37.682 46.549	0.642	0.923
Video Streaming	42.949 (±52.586)	34.379 (±59.056)	60.143 (±60.143)	25.344 (±43.461)	59.438 (±64.771)	20.044 (±39.063)	37.504 55.229	0.693	0.919
Entertainments	13.183 (±26.241)	13.917 (±32.069)	19.275 (±19.275)	10.321 (±25.06)	17.129 (±31.138)	9.988 (±25.768)	13.45 29.232	0.529	0.726
Average Smartphone Use	286.978 (±155.087)	316.967 (±151.638)	339.71 (±339.71)	285.535 (±135.141)	336.671 (±163.7)	280.612 (±140.49)	304.466 (±152.38)	0.93	NA

4.3 Correlations Analysis

Correlation analysis is a statistical approach that assesses the degree and direction of a relationship between two or more variables. It is extensively used in research to investigate how changes in one variable correlate with changes in another, providing insights into patterns and relationships without assuming causality. The Pearson correlation coefficient (r) is the most common measure of correlation. It quantifies the linear relationship between two continuous variables on a scale ranging from -1 to +1, where +1 indicates a perfect positive correlation, -1 indicates a perfect negative correlation, and 0 indicates no linear correlation [109]. Correlation analysis is frequently used by researchers as a preliminary phase in data analysis to uncover associations that may require further exploration or to support hypotheses.

In the current study, Spearman's rho correlation was used to evaluate the monotonic relationships between subjective well-being, dimensions of problematic internet use, and various categories of smartphone activity. Table 4.3 presents the correlation matrix among the studied variables, revealing several noteworthy patterns of association. The five items from the Satisfaction with Life Scale (SWLS) demonstrated strong positive intercorrelations, reflecting the internal consistency of the scale. The highest correlation was observed between *swls_1* and *swls_3* ($\rho = 0.687$, $\boldsymbol{p < .001}$), while other SWLS items also showed moderate to strong positive relationships, suggesting that these items reliably measure a common construct related to life satisfaction.

Across the table, the three dimensions of problematic internet use, Obsession, Neglect, and ControlDisorder, were consistently and negatively correlated with SWLS items. For example, Obsession had a notable negative correlation with swls_3 ($\rho = -0.329$, $p < .001$), while ControlDisorder was similarly negatively associated with multiple SWLS items, including swls_3 ($\rho = -0.230$, $p < .001$) and swls_1 ($\rho = -0.168$, $p < .01$). These findings suggest that higher levels of problematic internet use are associated with lower subjective well-being. Interestingly, Neglect showed weaker correlations with SWLS items and was not significantly associated with swls_4 or swls_5, suggesting that not all aspects of problematic use are equally detrimental to life satisfaction.

The intercorrelations among the PIU dimensions were strong and positive, indicating their conceptual overlap and mutual reinforcement. Obsession was strongly correlated with Neglect ($\rho = 0.424$, $p < .001$) and ControlDisorder ($\rho = 0.399$, $p < .001$), while Neglect and ControlDisorder were also positively associated ($\rho = 0.402$, $p < .001$). These results imply that individuals who score highly on one PIU dimension are likely to report higher levels on the others as well.

Smartphone usage variables displayed more heterogeneous correlations with SWLS and PIU. Categories such as COMMUNICATION and SOCIAL MEDIA showed weak negative correlations with SWLS items and small positive correlations with PIU traits. For example, COMM usage was negatively correlated with swls1 ($\rho = -0.181$, $p < .01$) and positively associated with ControlDisorder ($\rho = 0.181$, $p < .01$), indicating that frequent communicative app use may relate to lower well-being and higher behavioral dysregulation. On the other hand, SOCIAL use showed only marginal associations with SWLS, though it had weak positive correlations with PIU traits such as Neglect ($\rho = 0.162$, $p < .01$).

Gaming and video streaming apps showed more pronounced patterns. GAME usage had a significant positive correlation with ControlDisorder ($\rho = 0.172$, $p < .01$) and Neglect ($\rho = 0.132$, $p < .05$), while showing no significant relationship with any SWLS item. Conversely, VIDEO use was significantly negatively correlated with all SWLS items, particularly swls_4 ($\rho = -0.326$, $p < .001$), and positively related to all three PIU dimensions. This suggests that passive content consumption, such as video streaming, might be more closely tied to reduced well-being and problematic use patterns than interactive apps like gaming or communication.

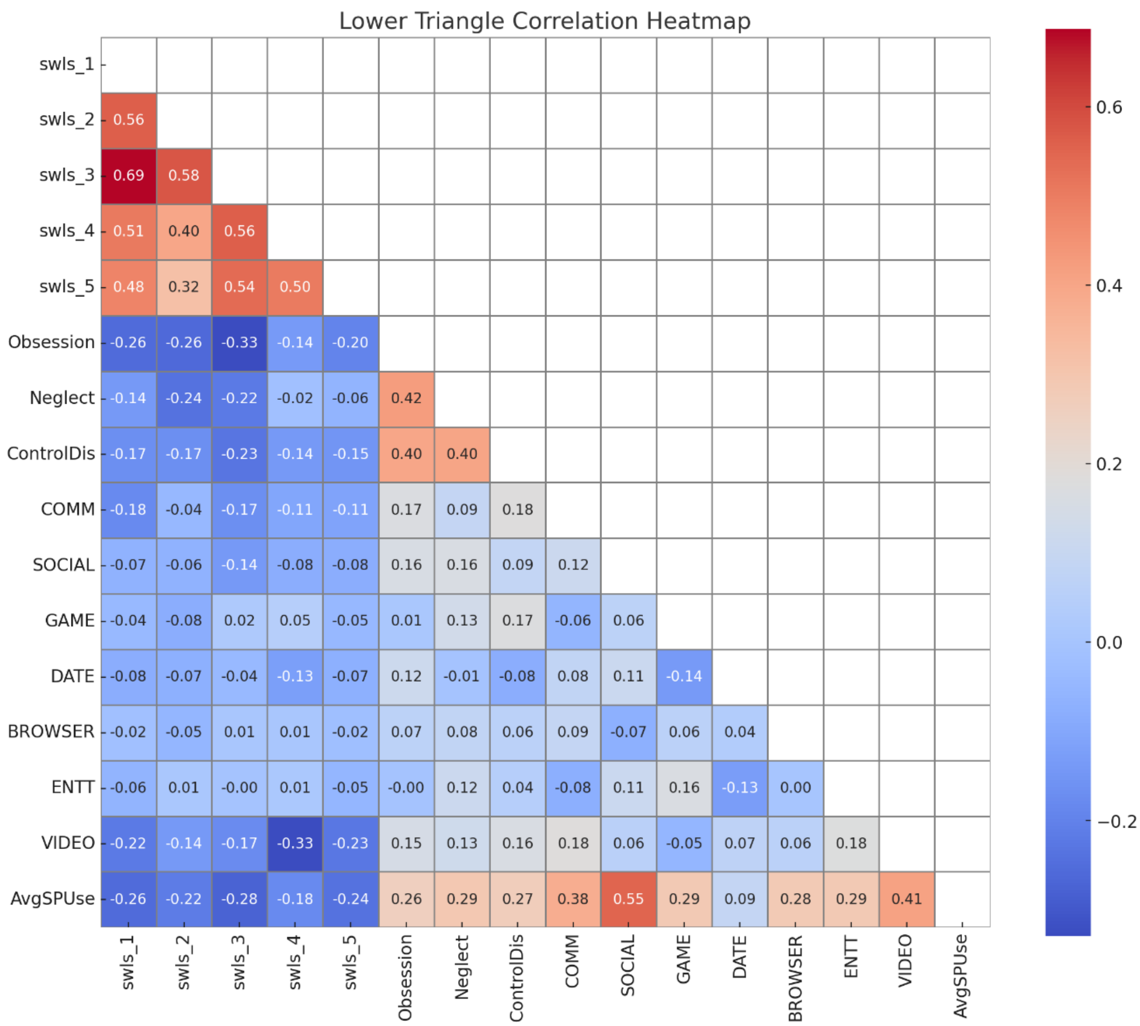

Figure 4.1: Pearson's Correlations heatmap

Some app categories, such as BROWSER and ENTERTAINMENT, showed little to no significant associations with SWLS or PIU variables. DATE usage also presented weak and inconsistent correlations, including a negative relationship with swls_4 ($\rho = -$

0.126, $p < .05$) and ENTT ($\rho = -0.130$, $p < .05$), suggesting specific behavioral patterns without broad implications across domains.

Finally, average screen time (AvgSPUse) demonstrated strong and consistent correlations across both well-being and problematic use domains. It was negatively associated with all SWLS items, particularly swls_3 ($\rho = -0.275$, $p < .001$), and positively associated with all PIU dimensions, such as Obsession ($\rho = 0.261$, $p < .001$) and ControlDisorder ($\rho = 0.269$, $p < .001$). It was also highly correlated with use of SOCIAL ($\rho = 0.552$, $p < .001$), COMM ($\rho = 0.379$, $p < .001$), and ENTT ($\rho = 0.287$, $p < .001$), reinforcing the notion that greater overall screen time is linked to digital over-engagement and lower subjective well-being.

4.4 Exploring the Interrelationships Among PIU Dimensions, SWL Items, and Category-Wise App Use Utilizing EGA

EGA was employed to examine the correlation structure among PIU dimensions, SWL items, and category-wise smartphone application usage. The analysis was based on a correlation estimator with the correlation method set to automatic selection, ensuring optimal adaptation to the data structure. A significance threshold was applied to identify meaningful connections within the network. To evaluate the reliability and stability of the network structure, a nonparametric bootstrap procedure with 1000 resamples was conducted. This approach allowed for the assessment of the robustness of edge weights, centrality indices, and cluster assignments. The Walktrap community detection algorithm was used to identify distinct clusters within the network, revealing coherent groupings of variables. Results were summarized using weights matrices, centrality and clustering tables, along with corresponding visual network plots. The analysis revealed complex patterns of association among the studied variables, offering a detailed view of the interplay between smartphone use and subjective well-being.

4.4.1 Network Characteristics: Nodes, Edges, and Sparsity in the EGA Analysis

Table 4.4 summarizes the network's structural features, including the number of nodes, non-zero edges, and sparsity. The network comprises 18 nodes, each representing an entity, component, or aspect of the system under assessment. These nodes are interconnected through edges, which signify relationships or interactions between them. Out of a total of 120 possible edges—calculated using the formula ($n(n–1)/2$) for an undirected network with $n = 18$ nodes—68 edges are non-zero, meaning they reflect active or meaningful connections. The sparsity of the network is calculated as (1 – (Number of non-zero edges / Total possible edges)), yielding a value of 0.433. This indicates that approximately 56.7% of the possible connections are absent, signifying a moderately sparse network. A sparsity value closer to 1 indicates a sparse network with fewer connections relative to its potential maximum, while a value closer to 0 indicates a densely connected network.

Table 4.3: Summary of Network

Number of nodes	Number of non-zero edges	Sparsity
18	68 / 120	0.433

4.4.2 Weights Matrix and Network Visualization

Table 4.5 presents the weights matrix detailing the strength and direction of associations among psychological variables (e.g., SWLS items, Obsession, Neglect, Control Disorder), behavioral tendencies, and various categories of smartphone application use. Each row and column represent a unique variable, such as individual satisfaction with life items ("swls_1" to "swls_5"), problematic use indicators, and app use categories including "COMMUNICATION," "SOCIAL MEDIA," "GAME," "DATE," "BROWSER," "ENTT" (Entertainment), "VIDEO," and "Avg Smartphone Use." The values in the matrix capture the magnitude and polarity of the partial correlations, with positive values indicating direct associations and negative values indicating inverse relationships. For instance, a strong positive weight (0.517) was found between "swls_1" and "SOCIAL MEDIA," suggesting that higher social media use is linked to increased satisfaction with life for that item. Conversely, negative weights such as –0.297 between "swls_1" and "ENTT" point to potential trade-offs, where increased entertainment app use is associated with lower satisfaction.

Notably, clusters of interrelated digital behaviors emerge from the matrix. Variables like "ENTT," "VIDEO," and "Avg Smartphone Use" show moderate to strong mutual associations (e.g., 0.597 between "ENTT" and "VIDEO," 0.532 between "VIDEO" and "Avg Smartphone Use"), hinting at a cohesive digital engagement pattern. Psychological dimensions also reveal important associations—such as "Neglect" correlating positively with "Control Disorder" (0.157) and "swls_4" (0.174)—which may reflect behavioral spillovers across constructs. The absence of values on the diagonal confirms that self-connections were excluded, in line with standard network modeling conventions.

These matrix patterns are visually depicted in the corresponding network graph (Figure 4.1), which highlights key connections and clusters among variables. The matrix provides a structural foundation for identifying central nodes, examining interdependencies, and interpreting how psychological and behavioral dimensions align with app usage profiles.

Table 4.4: Weighted Matrix

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	1
swls_1	0	0.385	0.402	0.275	0	0.39	0.314	0.288	0.28	0.517	0.45	-0.292	-0.293	-0.297	-0
swls_2	0.385	0	0	0	0	0	0	0	0	0	0	0	0	0	
swls_3	0.402	0	0	0.216	0	0	0	0.131	0.19	0	0.191	-0.216	0	-0.197	-0
swls_4	0.275	0	0.216	0	0	0	0.174	0.41	0.418	0	0.179	-0.18	-0.178	-0.253	-0
swls_5	0	0	0	0	0	0	-0.173	0	0.133	0	0	-0.138	-0.193	0	-0
Obsession	0.39	0	0	0	0	0	0.167	0	0	0	0.196	0	0	0	
Neglect	0.314	0	0	0.174	-0.173	0.167	0	0.157	0	0	0	0	0	0	
Control Disorder	0.288	0	0.131	0.41	0	0	0.157	0	0.441	0.166	0.13	-0.134	-0.244	-0.219	
COMMUNICATION	0.28	0	0.19	0.418	0.133	0	0	0.441	0	0.159	0.168	-0.278	-0.271	-0.343	-0
SOCIAL MEDIA	0.517	0	0	0	0	0	0	0.166	0.159	0	0	0	0	-0.138	
GAME	0.45	0	0.191	0.179	0	0.196	0	0.13	0.168	0	0	-0.237	-0.18	-0.201	-0
DATE	-0.292	0	-0.216	-0.18	-0.138	0	0	-0.134	-0.278	0	-0.237	0	0.585	0.705	0.
BROWSER	-0.293	0	0	-0.178	-0.193	0	0	-0.244	-0.271	0	-0.18	0.585	0	0.593	0.
ENTT	-0.297	0	-0.197	-0.253	0	0	0	-0.219	-0.343	-0.138	-0.201	0.705	0.593	0	0.
VIDEO	-0.189	0	-0.127	-0.145	-0.159	0	0	0	-0.147	0	-0.32	0.526	0.407	0.597	
Avg Smartphone Use	-0.244	0	-0.128	-0.171	0	0	0	0	-0.226	0	-0.213	0.506	0.357	0.564	0.

Figure 4.1 presents a network structure derived from EGA**,** mapping partial correlations among variables related to SWLS items, PIU dimensions, and smartphone application usage categories. Each node in the network represents a specific variable, while the edges between them denote the strength and direction of their associations. The color and thickness of these edges provide important visual cues, blue edges indicate positive relationships and red edges indicate negative ones, with thicker lines representing stronger connections.

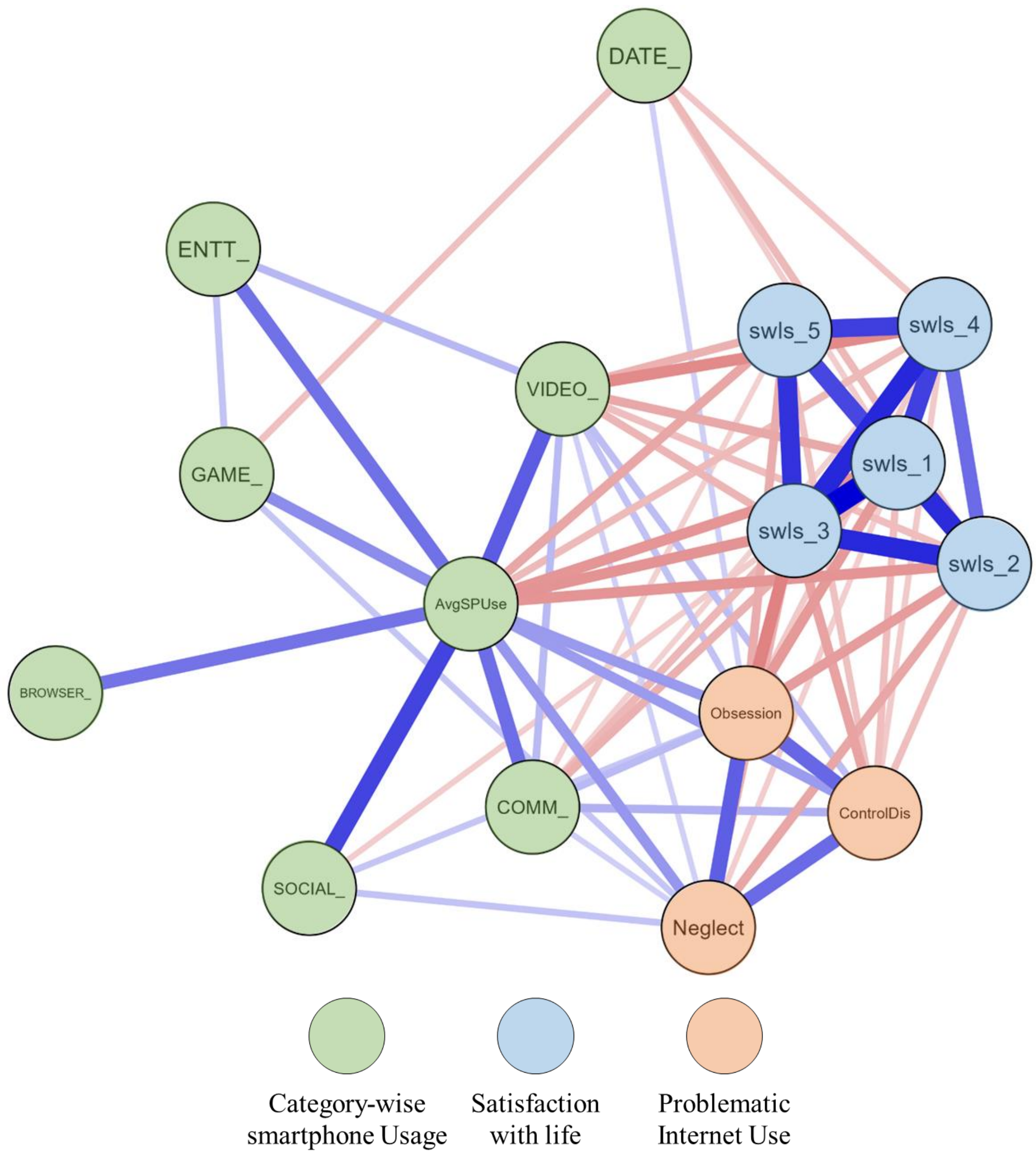

Figure 4.2: EGA Network Visualization

A clear and dense cluster of SWLS items (swls_1 to swls_5) appears in the top-right section of the network. These nodes, shaded in light blue, are tightly interconnected with thick blue edges, suggesting strong and consistent internal coherence among the different aspects of life satisfaction. Notably, swls_1, swls_2, and swls_3 are particularly central, reinforcing their integral role in reflecting subjective well-being. The strong associations within this cluster affirm the unidimensional nature of the SWLS scale and its robustness in measuring life satisfaction.

In contrast, problematic internet use dimensions**,** Obsession, Neglect, and Control Disorder**,** form a distinct cluster in the bottom-right quadrant. These nodes, shaded in orange, are also interlinked, indicating that individuals reporting one form of problematic use are likely to exhibit others as well. Among them, Neglect emerges as a highly connected node, particularly in its negative associations with both life satisfaction items and average smartphone use (AvgSPUse). This positioning suggests that feelings of neglect may mediate the adverse psychological impacts of excessive or uncontrolled smartphone engagement.

The left side of the network is dominated by app usage categories, such as SOCIAL, COMM, GAME, ENTT, VIDEO, and BROWSER. These nodes, colored in green, are mostly connected through the central node AvgSPUse, which acts as a major hub. The strong blue edges between AvgSPUse and various app categories indicate that higher overall screen time is consistently associated with greater use across entertainment, communication, and media platforms. This centrality of AvgSPUse underscores its role as a behavioral anchor within the network, linking daily habits to broader psychological outcomes.

However, the connections between AvgSPUse and psychological variables are more nuanced. While positively associated with media consumption (e.g., ENTT, VIDEO, SOCIAL), AvgSPUse also shows negative correlations with SWLS items and Neglect**,** reflecting the potential psychological trade-offs of excessive digital engagement. The red edges connecting AvgSPUse with swls_1 and swls_3 suggest that higher screen time may coincide with lower life satisfaction. Similarly, the strong red link with Neglect supports the notion that overuse can lead to feelings of disengagement or personal neglect.

The network also reveals meaningful bridges between clusters. For example, swls_1 and swls_3 serve as links between the well-being and psychological dysfunction clusters, while Neglect connects PIU dimensions to both behavioral and well-being nodes. These bridges indicate that certain key variables may mediate broader relationships, helping to explain how digital behaviors translate into psychological outcomes.

4.4.3 Centrality Analysis: Roles and Importance of Variables in the Network

The centrality Table 4.6 and corresponding plots Figure 4.2 offer a detailed assessment of the relative importance and network positions of each variable using four centrality metrics: betweenness, closeness, strength, and expected influence. Each metric provides a unique perspective on the role a variable plays within the overall network structure.

Betweenness centrality, which indicates how frequently a node lies on the shortest paths between other nodes, shows that *AvgSPUse* (3.622) has the highest value. This suggests that average smartphone use acts as a critical intermediary connecting different parts of the network. Conversely, variables such as *DATE*, *ENTT*, and *SOCIAL* all show low betweenness values (–0.364), indicating marginal roles in bridging other nodes.

Closeness centrality, measuring how near a variable is to all others in terms of path length, also places *AvgSPUse* (2.219) at the center of the network, followed by *swls_3* (1.221) and *swls_1* (0.910). In contrast, *DATE* (–2.129), *GAME* (–0.855), and *BROWSER* (–0.810) are more distant, suggesting lower accessibility and integration within the network.

Strength centrality, which captures the sum of the absolute edge weights directly connected to a node, identifies *AvgSPUse* (1.712) and *swls_3* (1.323) as the most directly connected variables. In contrast, *BROWSER* (–1.524) and *ENTT* (–1.243) show minimal direct connectivity, placing them on the network's periphery.

Expected influence, which incorporates both the magnitude and direction (positive or negative) of connections, highlights *AvgSPUse* (2.487) and *Neglect* (0.827) as having the most substantial overall influence on other variables. Notably, *DATE* (–2.366) and *VIDEO* (–1.030) exhibit strongly negative expected influence, suggesting a suppressive or distancing effect within the network.

The visual centrality plots corroborate these results, clearly positioning *AvgSPUse* as a dominant node across all centrality indices. Satisfaction-related variables like *swls_1*, *swls_3*, and *swls_5* also demonstrate consistently moderate to high centrality scores, reflecting their substantial involvement in the network. In contrast, variables such as *DATE*, *BROWSER*, and *SOCIAL* consistently show low values across all metrics, indicating peripheral involvement.

Table 4.5: Centrality measures per variable

	Network			
Variable	Betweenness	Closeness	Strength	Expected influence
AvgSPUse	3.622	2.219	1.712	2.487
BROWSER	-0.364	-0.810	-1.524	-0.601
COMMUNICATION	-0.364	-0.441	-0.443	-0.453
SOCIAL	-0.364	-0.300	-1.070	0.011
DATE	-0.364	-2.129	-1.210	-2.366
ENTT	-0.364	-0.787	-1.243	0.108
GAME	-0.364	-0.855	-1.066	-0.112
VIDEO	-0.364	0.078	0.066	-1.030
Neglect	-0.364	-0.258	-0.044	0.827
Obsession	-0.291	0.413	0.517	-0.333
Control Disorder	-0.364	-0.170	0.170	0.094
swls_1	-0.291	0.910	1.086	0.288
swls_2	0.374	0.808	0.707	-0.219
swls_3	0.448	1.221	1.323	0.219
swls_4	-0.217	0.021	0.589	0.537
swls_5	-0.364	0.080	0.430	0.541

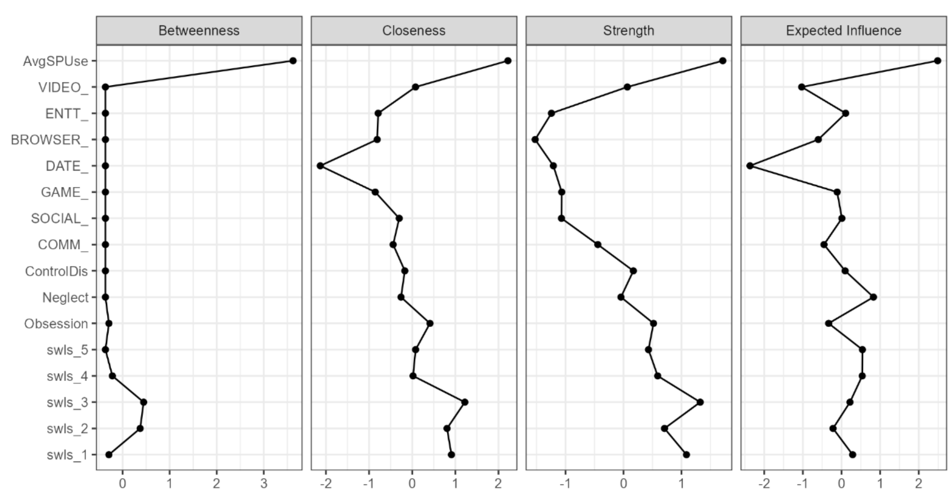

Figure 4.3: Centrality Plot

4.4.4 Clustering Analysis: Structural Cohesion Across Network Models

The clustering coefficients presented in the Table 4.7 and accompanying plot in Figure 4.3 evaluate the local interconnectedness of variables across four network models: Barrat**,** Onnela**,** Watts-Strogatz (WS)**,** and Zhang. These models highlight how individual nodes—representing variables such as subjective well-being (swls_1 to swls_5), problematic internet use dimensions (Obsession, Neglect, ControlDisorder), and category-specific smartphone use (e.g., COMMUNICATION, SOCIAL, MUSIC, VIDEO)—are embedded within local network neighborhoods.

Among the subjective well-being variables, the Onnela model reveals strong clustering, particularly for *swls_5* (1.355) and *swls_3* (0.975), indicating a tightly interconnected structure within this dimension. Similar trends are observed in the Zhang model, where *swls_5* (1.287) and *swls_4* (0.910) exhibit the highest coefficients. The WS model shows moderately high clustering values for these variables (e.g., *swls_5* = 1.038), while the Barrat model presents slightly lower but still positive clustering (e.g., *swls_5* = 0.946 and *swls_4* = 0.552), suggesting consistent local cohesion across models.

In contrast, psychological traits such as *Obsession* and *Neglect* exhibit low or negative clustering values, especially in the Onnela (–0.042 and –0.244, respectively) and Zhang models (–0.126 and –0.128). *Control Disorder* is an exception, showing positive clustering in the Barrat (0.317) and WS (0.342) models, indicating moderate local connectivity.

Digital activity categories display more heterogeneous clustering behavior. *MUSIC*, which previously showed high clustering, is not listed in this version of the table, but *SOCIAL_* and *COMM_* now demonstrate strong clustering across all models. For instance, *SOCIAL_* shows values of 1.027 (Barrat), 0.655 (Onnela), and 1.150 (WS), highlighting its central role in local clusters. Similarly, *COMM_* ranges from 0.228 (Onnela) to 0.926 (WS), reinforcing its consistent integration within dense substructures.

On the other end of the spectrum, variables such as *BROWSER_* and *GAME_* exhibit significantly negative clustering coefficients in all four models, with *BROWSER_* showing extremely low values (e.g., –2.936 in Barrat and –2.725 in Zhang), indicating fragmentation or isolation in the network. *AvgSPUse* also demonstrates negative clustering across models (e.g., –0.919 in Barrat, –1.396 in Zhang), suggesting that overall screen time does not form a cohesive sub-network.

The clustering plot visually reinforces these findings, highlighting the variability of clustering behavior across models and variables. Nodes such as *swls_5*, *COMM_*, and *SOCIAL_* stand out as highly clustered, whereas *BROWSER_*, *GAME_*, and *AvgSPUse* are consistently peripheral and loosely connected.

Table 4.6: Clustering measures per variable.

	Network			
Variable	Barrat	Onnela	WS	Zhang
Obsession	0.106	-0.042	0.048	-0.126
Neglect	0.113	-0.244	-0.017	-0.128
ControlDis	0.317	0.061	0.342	-0.045
COMM_	0.885	0.228	0.926	0.517
SOCIAL_	1.027	0.655	1.150	0.537
GAME_	-1.154	-1.283	-1.274	-0.978
DATE_	-0.608	-0.968	-0.466	-0.359
BROWSER_	-2.936	-2.627	-2.891	-2.725
ENTT_	0.073	0.092	-0.197	0.700
VIDEO_	0.265	-0.033	0.269	0.159
AvgSPUse	-0.919	-0.539	-0.715	-1.396
swls_1	0.470	0.807	0.416	0.568
swls_2	0.460	0.846	0.432	0.694
swls_3	0.404	0.975	0.416	0.386
swls_4	0.552	0.717	0.522	0.910
swls_5	0.946	1.355	1.038	1.287

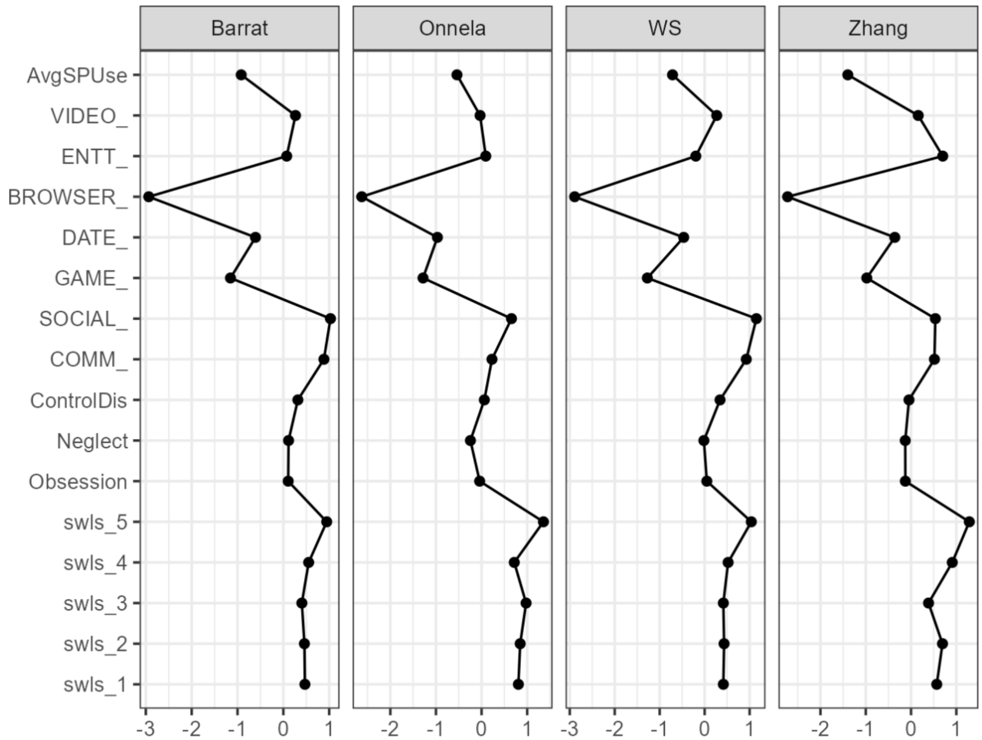

Figure 4.4: Clustering Plot.

4.5 Discussion

This study offers a comprehensive exploration of the complex relationships between AveSPUse, category-wise smartphone app use, PIU, and SWL indicators employing advanced network analysis. The integration of both quantitative methods and network analysis enhances the understanding of how digital behaviors influence psychological well-being.

4.6 Discussion of Smartphone App Usage

4.6.1 Category-Wise Apps Use

The usage of communication apps, such as messaging and calling platforms, is high across all demographics, with females reporting slightly higher usage than males. This aligns with findings from [110], who observed that females tend to use communication technologies more for social purposes. Research consistently shows that females are generally more inclined to use communication technologies to maintain social bonds, express emotions, and sustain interpersonal relationships. This tendency reflects broader psychosocial theories that suggest women often prioritize relational communication, while men may use digital tools more instrumentally.

Emerging adults also show high usage, consistent with studies emphasizing their reliance on digital communication [111]. The Shapiro-Wilk test indicates that the data is non-normally distributed, but transformations bring it closer to normality, as evidenced by the improved Shapiro-Wilk statistics.

Social media apps exhibit the highest usage among females and students. This trend is supported by studies like those of [112], which found that younger populations and females are the most active social media users. Interestingly, non-students and adults report lower usage, suggesting that social media engagement may decrease with age and as individuals transition to professional roles. Literature aligns with these patterns, although the non-normal distribution of data suggests outliers or skewed usage behaviors.

Gaming apps show relatively low usage across all groups, with males slightly outpacing females. Students, particularly males, tend to engage more with gaming apps, which is consistent with findings from [113], who highlighted the prevalence of gaming among young males. However, the overall low usage may reflect a shift in entertainment preferences, as streaming services gain popularity.

The usage of dating apps is minimal, with higher engagement among males and emerging adults. This is in line with studies by [114], which report that dating apps are most popular among young adults seeking romantic or social connections. However, the extremely low usage among non-students and adults suggests that such apps are less relevant to those in long-term relationships or with different social priorities.

Browsing apps show significant engagement, with males reporting slightly higher usage than females. This pattern aligns with findings by [115], which indicate that men are more likely to use browsing apps for informational purposes. The relatively high Shapiro-

Wilk statistic after transformation suggests that browser usage data is moderately aligned with normality assumptions.

Video streaming apps have high usage among students and emerging adults, aligning with the findings of [116], which highlight the role of media consumption in leisure activities for younger populations. Female users show slightly higher usage, possibly reflecting gender differences in media preferences.

General, the patterns observed in the data align with existing literature, confirming established trends in smartphone app usage. Minor discrepancies, such as low dating app usage among emerging adults or unexpected changes in video streaming habits, could be due to cultural or environmental variables unique to the sample population. Additional research, such as qualitative or cross-cultural comparisons, could yield deeper insights.

4.6.2 Discussion for EGA Analysis

The EGA analyzed the dataset's structure, including three aspects of PIU (Obsession, Neglect, Control Disorder), SWL items, and smartphone use categories (e.g., Social, Communication, Gaming, etc.). The research produced several clusters, indicating linkages between variables and their impact on larger categories.

4.6.3 PIU Dimensions

The EGA identified three main dimensions of PIU: obsession, neglect, and control disorder. Previous research suggests that PIU is a multidimensional construct that includes cognitive, emotional, and behavioral dysregulation. These dimensions align with this theory.

Obsession refers to constant, intrusive thoughts about internet use and an inability to keep away from engaging in online activities. This supports Caplan's theory of poor self-regulation, which suggests that excessive internet use is often due to psychological dependence. Research indicates that excessive internet use might cause emotional distress and impair daily routines and social connections. Obsession had a moderate centrality in the network, indicating a strong impact on PIU and related psychological consequences. Cognitive-behavioral therapies are crucial for recovering control over excessive internet use, as highlighted by this study.

The Neglect component refers to the tendency to overlook personal, academic, or professional responsibilities due to excessive internet use. It is widely recognized in the literature as a core dimension of problematic internet use (PIU), often leading individuals to prioritize online activities over essential real-life obligations. However, in the present EGA analysis, Neglect did not emerge as the most central or influential component in the network. Its centrality values across metrics such as betweenness, closeness, strength, and expected influence were relatively low or mixed, indicating a more peripheral role in the network structure. While it maintained moderate positive correlations with other PIU components, its direct connection to life satisfaction variables was limited. This finding suggests that while Neglect remains a critical symptom of PIU, its impact on overall psychological well-being and life satisfaction may not be as pronounced as previously assumed in some studies. Interventions aiming to address neglectful behaviors should still be considered, particularly in combination with other more central components such as Obsession **or** Control Disorder, to comprehensively manage PIU and its effects.

The Control Disorder dimension reflects an inability to regulate or limit internet use despite recognizing its harmful effects. In the present study, Control Disorder demonstrated relatively low centrality across the EGA network metrics, suggesting it played a more peripheral role in the network structure. Although it shared moderate correlations with life satisfaction and other PIU variables, its direct influence on overall well-being appeared less pronounced than initially hypothesized. This finding implies that, while lack of control is a recognized characteristic of PIU, its network-level impact on psychological outcomes may be secondary to other factors, such as Obsession or overall screen time. Nevertheless, addressing control-related behaviors remains essential. Research by [117] also highlights that individuals with poor self-regulation are more prone to psychological distress and reduced life satisfaction. Targeted interventions, such as digital self-monitoring tools, screen time restrictions, and behavior modification strategies, may help individuals regain a sense of control and mitigate compulsive online behaviors.

The interconnections between Obsession, Control Disorder reflect the multidimensionality of PIU. This supports [54] cognitive-behavioral model of internet addiction, which emphasizes the relationship between maladaptive cognitions and behavioral dysregulation in exacerbating functional impairments. The results suggest that interventions targeting one dimension, such as reducing obsessive interne have cascading benefits for improving self-regulation and mitigating neglect. These findings underscore the importance of comprehensive intervention strategies that address all facets of PIU.

4.6.4 Discussion of Satisfaction with Life

The **EGA** revealed that the **SWL** items clustered together, indicating a unidimensional structure. This finding aligns with the conceptual framework proposed by [118], which defines life satisfaction as an individual's cognitive appraisal of their life**,** based on self-defined criteria. The clustering of the SWL items suggests strong shared variance, supporting the interpretation that these items collectively measure a single underlying construct, namely, overall life satisfaction. This structural coherence reinforces the psychometric validity of the SWLS in capturing the global evaluation of one's life.

4.6.4.1 Central Role of SWL Items

Among the five SWL items, **SWL_3** ("I am satisfied with my life") demonstrated the highest centrality, with a strength of 1.496. This aligns with previous research suggesting that global satisfaction items tend to have the strongest predictive power in assessing life satisfaction [119]. The strong centrality of SWL_3 indicates its pivotal role in the SWL construct, serving as a robust indicator of general life contentment. Furthermore, **SWL_1** ("In most ways, my life is close to my ideal") and **SWL_5** ("If I could live my life over, I would change almost nothing") also exhibited notable centrality, reinforcing their relevance in evaluating subjective well-being.

4.6.5 Discussion of Category-Wise Smartphone Use

The EGA identified diverse smartphone usage patterns across areas such as social media, communication, gaming, entertainment, video, and others. These categories form separate clusters, reflecting their unique usage behaviors and psychological implications. The findings underscore the multidimensional nature of smartphone usage, where each category fulfills specific needs and contributes differently to digital well-being and life satisfaction.

Regarding apps, Social media and communication apps emerged as closely related categories in the network, highlighting their intertwined role in fostering virtual social interactions. This finding is consistent with the uses and gratifications theory, which posits that social media and communication platforms fulfill the basic human need for social connectedness [120]. While these apps provide opportunities for maintaining relationships and receiving social support, excessive use has been linked to negative psychological outcomes, such as reduced sleep quality, increased anxiety, and lower life satisfaction [121]. In the current study, the high centrality of these categories indicates their significant influence on overall smartphone use patterns and their potential impact on satisfaction with life. The Gaming category exhibited a distinct pattern in the network, suggesting unique behavioral and psychological attributes**.** Gaming apps are commonly used for entertainment, stress relief, and escapism [122]. However, excessive gaming has been associated with problematic behaviors, including gaming disorder, which can interfere with daily responsibilities and reduce overall life satisfaction [123]. In the current study, Gaming showed low centrality and negative clustering coefficients, indicating a more peripheral role in the network. While it may not be the most influential category, its potential impact on problematic smartphone use and well-being remains relevant. Interventions aimed at promoting balanced gaming habits—such as setting time limits, encouraging offline activities, and fostering awareness—may help mitigate its adverse effects. Similarly, entertainment and video streaming apps formed another cluster, reflecting their role in providing leisure and relaxation. These apps are often used to cope with stress and unwind, which can contribute positively to mental health in moderation [124] However, binge-watching behaviors associated with video apps, such as prolonged usage and disrupted sleep schedules, have been linked to lower sleep quality and reduced productivity [125]. The network analysis indicates that these categories are moderately related to problematic internet use components including Neglect and Control Disorder, which might disrupt daily routines if used excessively.

The study found that smartphone usage by category significantly impacts users' digital well-being. The clustering of app categories emphasizes the importance for targeted efforts to address specific usage patterns. For instance, promoting mindful social media use and encouraging balanced communication can foster healthier online interactions, while guiding users toward moderated gaming and entertainment habits can help prevent excessive use.

4.6.6 Relationships Between PIU, SWL, and Category-Wise Smartphone Apps

The study found significant correlations between PIU, SWL, and smartphone app categories, highlighting the impact of digital habits on well-being. The network analysis revealed intricate relationships between these dimensions, shedding light on the psychological and behavioral factors that contribute to PIU and its effect on life satisfaction.

4.6.6.1 PIU and SWL

The study demonstrated a significant negative correlation between PIU aspects (obsession, neglect, and control disorder) and SWL. Excessive internet use can negatively impact life satisfaction by reducing mental health, social relationships, and productivity[121]. Excessive smartphone use can lead to unhappiness in important life domains, including employment, relationships, and health [126]. Control Disorder, characterized by difficulty regulating internet use, was found to be substantially associated with lower SWL, highlighting the psychological impact of obsessive digital activities ([117]). These findings highlight the significance of addressing PIU to improve life satisfaction and well-being.

4.6.6.2 PIU and Category-Wise Smartphone Apps

This analysis revealed that different smartphone app categories were variably associated with PIU dimensions. Social media and Communication Apps categories had a significant positive correlation with Obsession and Neglect. Unnecessary social media use can lead to obsessive thoughts and neglect of tasks due to the fear of missing out (FoMO) (Elhai et al., 2017) Gaming Apps**'** addictive nature can affect self-regulation, directing to a positive correlation with Control Disorder. This study Lemmens et al. (2015) found that gaming addiction can lead to losing track of time and putting virtual successes ahead of real-life duties. Furthermore, Entertainment and Video Apps categories were weakly related to PIU, their connection to Neglect shows that binge-watching can disrupt time management and lead to procrastination, ultimately contributing to negative internet behaviors [127].

4.6.6.3 SWL and Category-Wise Smartphone Apps

The relationships between SWL and smartphone app usage varied depending on the app category. Social media and Communication Apps showed a negative correlation with SWL. Extreme use of social applications can lead to social comparison, low self-confidence, and anxiety, resulting in decreased life satisfaction [121]. Balanced use can improve SWL by promoting social relationships and emotional support [128]. Gaming Apps had a small negative association with SWL, showing that, while it might provide relaxation and release stress, excessive gaming can reduce life satisfaction by encouraging isolation and neglect [124]. Entertainment and Video Apps had a mixed relationship with SWL. While enough recreational use can improve mental health, excessive use frequently impairs sleep and productivity, resulting in dissatisfaction in other areas of life [127].

4.6.6.4 Interconnections Between PIU, SWL, and App Use

The network analysis revealed substantial connections between PIU, SWL, and smartphone usage categories. Excessive use of social media apps was connected to Neglect, resulting in unfavorable effects on SWL. PIU may play a mediating function in the association between specific app use and life satisfaction. Excessive gaming app use has been connected to Control Disorder, which can decrease self-regulation and increase psychological distress, thereby reducing SWL. [54] cognitive-behavioral model of internet addiction suggests that inappropriate internet use might negatively impact well-being by causing cognitive distortions and emotional dysregulation. This discussion has been summarised in the following table.

Table 7: Summary of the discussion and findings.

Topic	**Finding Summary**	**Alignment with Literature**

Communication Apps	High usage, especially among females and emerging adults.	Aligned [110]
Social Media Apps	Highest usage among females and students; lower usage among adults/non-students.	Aligned [129]
Gaming Apps	Low usage overall, slightly higher among males and students.	Not aligned
Dating Apps	Minimal usage, higher among males and emerging adults.	Aligned [114]
Browsing Apps	Moderate use, slightly higher among males.	Aligned [115]
Video Streaming	High among students and emerging adults; females slightly higher.	Aligned [116]
PIU - Obsession	Moderate centrality; most influential on PIU.	Aligned [117]
PIU - Neglect	Peripheral role in network; moderate correlation with other components.	Partially aligned; less central than in prior literature
PIU - Control Disorder	Peripheral role; moderate link to SWL.	Partially aligned [117]
SWL Structure	Unidimensional structure; high internal consistency.	Aligned [118]
SWL Item Centrality	SWL_3 most central; followed by SWL_1 and SWL_5.	Aligned [119]

App Use & PIU	Social and Communication apps linked to Obsession & Neglect; Gaming linked to Control Disorder.	Aligned (Elhai et al., 2017)
App Use & SWL	Negative association with excessive Social, Gaming, Video usage.	Aligned [121]
Interconnections	PIU mediates between app use and SWL; Obsession and Control Disorder key mediators.	Our findings and possible future direction

4.7 Implications of This Study for Digital Well-Being

This study provides valuable insights on enhancing digital well-being by promoting a healthy and balanced relationship with technology to improve overall quality of life. This study identifies actionable ways for individuals, researchers, and policymakers to limit the harmful effects of excessive digital involvement by analyzing the links between PIU, SWL, and smartphone categories.

Targeted interventions should address the three unique components of PIU: obsession, neglect, and control disorder. Tailored techniques can assist users regain control over their digital activities, as these aspects have a harmful effect on SWL. Mindfulness-based therapies and digital detox practices may reduce Obsession's intrusive thoughts, while time management and offline activity promotion can help with Neglect. Using self-monitoring apps and setting usage restrictions helps enhance self-regulation and minimize compulsive behaviors in Control Disorder.

The study focuses on healthy smartphone usage across app categories. Excessive use of social media, gaming, and entertainment apps has been linked to increased PIU and lower SWL. To mitigate these impacts, users can establish time restrictions for social media use and enable focus modes to prevent abuse. Limiting games and entertainment can lead to better sleep and productivity. The measures try to balance digital involvement and real-life duties.

Educational programs are essential for improving digital well-being. Digital literacy and awareness programs can educate people on the consequences of excessive smartphone use and provide solutions to manage PIU. Integrating these programs into schools, businesses, and communities helps promote healthy digital behaviors among various populations. Promoting healthy digital activities, including using applications for fitness, education, or productivity, can enhance a sense of purpose and increase SWL. Engaging in virtual support groups or learning communities can improve emotional well-being.

Technology developers and designers are responsible for designing user-centric applications that promote digital well-being. Personalized screen time recommendations, use insights, and focus modes can help consumers manage their smartphone usage. Including well-being triggers, like reminders to take breaks or engage in offline activities, can help promote beneficial habits. Designing technology with user well-being in mind promotes life happiness, rather than detracting from it.

Policymakers may promote responsible technology use and ethical app design through laws. Encouraging developers to provide self-regulation tools and accessible usage data can promote healthy digital behaviors. Supporting research and sponsoring intervention programs can help address the issue of excessive smartphone use and its impact on health. Policies that foster collaboration among stakeholders—researchers, developers, and mental health professionals—can create a holistic framework for improving digital well-being.

This study emphasizes the need for more research on the long-term effects of PIU and smartphone use on digital well-being. Longitudinal research can provide insight into how digital behaviors change over time and their correlation with SWL. Cross-cultural research is crucial for understanding how cultural norms and values affect relationships and developing culturally appropriate solutions. Future study aims to better comprehend the complex relationship between digital technology and well-being.

In conclusion, this study emphasizes the importance of keeping a healthy connection with technology to enhance digital well-being. To reduce the harmful impacts of excessive smartphone use, stakeholders can undertake targeted interventions, promote healthy digital practices, and build user-centric solutions. These projects aim to improve persons' life happiness and well-being, using technology to enhance rather than diminish their quality of life.

CHAPTER 5
CONCLUSION, LIMITATIONS, AND FUTURE DIRECTIONS

This study's major finding is the identification of a complex, interrelated structure between PIU, SWL, and category-wise smartphone app usage, revealed through advanced EGA. The network analysis confirmed that different app categories (e.g., social media, communication, gaming, video, and entertainment) are uniquely associated with specific dimensions of PIU (obsession, neglect, and control disorder) and that these, in turn, are significantly and negatively correlated with life satisfaction. Notably, the Obsession dimension emerged as the most central component in the PIU network, suggesting that compulsive, intrusive internet use has the strongest and most direct influence on psychological well-being. Additionally, the SWL items formed a cohesive, unidimensional cluster, validating the integrity of the life satisfaction construct. The study further highlighted that excessive use of social and communication apps is most strongly linked to increased PIU and reduced SWL, indicating that digital behaviors driven by social connectivity can become maladaptive when not moderated. These findings underscore the central mediating role of PIU in the relationship between app usage and life satisfaction, and emphasize the need for targeted interventions focusing on digital self-regulation, balanced app use, and strategies for mitigating compulsive digital engagement to support and enhance digital well-being.

5.1 Limitations

This study has some limitations. The sample size and demographic composition may restrict the generalizability of the results. A more diversified sample, including individuals of various ages, cultural backgrounds, and socioeconomic positions, might improve the results' applicability. Second, the study used cross-sectional data, which limits the capacity to draw causal conclusions between PIU, SWL, and smartphone usage patterns. Longitudinal data highlight a better picture of how these interactions change over time. Issues like cultural problems which may impact smartphone usage and well-being, were not taken into consideration. In determining digital habits, cultural norms and values have a vital influence, thus future research should include cross-cultural comparisons. Finally, the study relied on self-reported data for smartphone use and life satisfaction, which could be skewed due to social interest and incorrect recollection.

5.2 Future Directions

Future research should overcome the limitations highlighted above to expand on the findings of this study. To determine the universality or variability of observed correlations, the sample should comprise participants from varied demographics and cultural backgrounds. Longitudinal studies are needed to investigate the causal relationship between PIU, SWL, and smartphone use over time. This research could look at how life events, digital habits, and technological improvements impact these dynamics. Future research should include objective measurements of smartphone usage, like screen time tracking or app usage logs, to validate self-reported data and improve accuracy.

Cross-cultural research can help understand how cultural differences impact the association between PIU, SWL, and smartphone use. This research could show culturally specific aspects shaping digital well-being, allowing for the development of targeted solutions. Finally, future study might investigate how psychological variables like emotional intelligence, resilience, and digital literacy can overcome the negative effects of PIU while also promoting digital well-being. Addressing these areas will lead to more in-depth insights and effective solutions for improving technology connections.

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