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Impact of Digital Engagement on Mental Health and Neuroplastic Changes in Adults

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ABSTRACT

In the digital era, digital engagement has become an intrinsic part of daily life, particularly among young adults and professionals. However, the impact of screen usage on mental health and brain development remains understudied in Nepal. This study examines the relationship between screen time, psychological well-being, and neuroplasticity among adults in Kathmandu. Utilizing data from 359 participants aged 18 and above, we assessed psychological well-being using the WHO-5 Well-Being Index and evaluated maladaptive and adaptive neuroplasticity through self-reported digital behaviors. Regression analyses revealed that smartphone and social media usage had a weak negative correlation with psychological well-being ($\beta = -0.267$, $p < 0.05$; $\beta = -0.244$, $p < 0.05$) and weak to moderate positive correlation with maladaptive neuroplasticity ($\beta = 0.342$, $p < 0.05$; $\beta = 0.411$, $p < 0.05$). Conversely, engagement with educational content had a weak positive correlation with adaptive neuroplasticity ($\beta = 0.215$, $p < 0.05$), and work-related digital content was weakly negatively correlated with maladaptive neuroplasticity ($\beta = -0.098$, $p < 0.05$). Among students, excessive smartphone and social media use impaired cognitive development, whereas educational content and gaming had positive neurological effects. Among employed individuals, structured digital engagement (work-related tasks) mitigated the negative impact of screen time, whereas compulsive digital behaviors led to cognitive strain. While specific content promotes cognitive growth, habitual social media and excessive smartphone use may lead to detrimental emotional and neural outcomes. These findings show the importance of purposeful and balanced digital engagement to support mental health and cognitive resilience. Public health interventions should focus on digital literacy, mindful screen use, and promoting constructive content consumption to mitigate the adverse effects of excessive screen exposure.

Keywords: digital engagement, screen time, psychological well-being, neuroplasticity, social media, mental health

Introduction

The digital age has transformed people's daily lives worldwide, including in Nepal. Increasing access to smartphones, laptops, and internet-enabled devices has brought about dramatic changes in communication, information consumption, and entertainment. Screen time has become an unavoidable component of adult life, from scrolling through social media to watching television or completing work on laptops. Undergraduates in Nepal have an average of 7.12 hours per day of screen time (Maharjan et al., 2023). While digital connectivity has enabled access to information and enhanced productivity, it has also raised critical concerns regarding its impact on emotional well-being and brain development.

Problem Statement

Global research increasingly points to the psychological consequences of prolonged screen use, such as increased anxiety, depression, loneliness, and reduced attention span (Neophytou et al., 2019). Yet, the effects of screen time are not uniform – they can vary significantly depending on the type of device being used (e.g., smartphone, laptop/desktop, TV, gaming console) and the nature of the content consumed (e.g., TV shows, social media, gaming, educational, work-related content). Some digital activities may stimulate the brain positively, while others might reinforce negative emotional states (Twenge & Farley, 2021). Despite the relevance of this distinction, few studies in Nepal have investigated how different devices and content types affect mental well-being. Given the digital transformation occurring in Nepal, there is an urgent need to investigate how screen time influences the psychological well-being of Nepali adults, specifically in Kathmandu.

Relevance of Neuroplasticity

At the core of this investigation is the concept of neuroplasticity. It is the brain's ability to adapt and rewire itself based on repetitive experiences and inputs. Repetitive exposure to certain types of digital content (e.g., social media, news feeds, gaming) may reinforce maladaptive neural patterns, while intentional and balanced screen use may support positive mental stimulation and learning (Mathiak & Weber, 2006). This study considers neuroplasticity a key conceptual framework to interpret the cognitive and emotional changes associated with prolonged screen engagement.

Objectives of the Study

This research aims to:

1. Assess the average screen time of adults in Kathmandu by device type and content category.
2. Examine how different types of devices (e.g., smartphone, laptop/desktop, TV, gaming console) relate to psychological well-being.
3. Examine how specific content types (e.g., TV shows, social media, gaming, work-related tasks, educational content) relate to psychological well-being.
4. Interpret the findings using the framework of neuroplasticity to explain potential cognitive and emotional effects.

Research Questions

1. What is the average screen time of adults in Kathmandu across various devices and content types?
2. How does screen time on different devices correlate with psychological well-being indicators?
3. Do certain content types have a more significant impact on psychological well-being?
4. How can neuroplasticity explain the observed emotional and cognitive outcomes associated with different digital habits?

Significance of the Study

This research contributes to the growing discourse on digital wellness by highlighting how not all screen time is created equal. Examining both device use patterns and content consumption offers a more granular understanding of the psychological risks and benefits of digital behavior. Framing the analysis within the concept of neuroplasticity offers a scientific explanation of how screen habits may reshape cognitive and emotional functioning over time. The findings are expected to inform public health awareness, promote digital literacy, and guide interventions aimed at improving mental health in a rapidly digitizing Nepal.

Literature Review

Conceptual Overview

Screen Time

Screen time refers to the duration individuals spend engaging with devices such as smartphones, computers, televisions, and gaming consoles. It encompasses both active (e.g., work-related tasks, educational activities) and passive (e.g., watching videos, scrolling through social media) interactions. In the digital era, screen time has become integral to daily life, influencing various aspects of human behavior and health. Excessive screen time has been linked to adverse outcomes, including reduced physical activity, sleep disturbances, and negative impacts on mental health (Carolina et al., 2024). While screen time is often quantified in terms of hours per day, it is important to consider the type of device, nature of content, and context of use to fully understand its impact on psychological well-being.

Psychological Well-being

Psychological well-being is a multifaceted construct that includes emotional, cognitive, and social dimensions. Elevated screen time has been linked to increased symptoms of depression and anxiety. For instance, a study found that adolescents engaging in more than 4 hours of screen time daily exhibited higher levels of these symptoms compared to those with less screen exposure (Carolina et al., 2024). Prolonged screen use, especially without breaks, can lead to heightened stress levels due to constant cognitive engagement and reduced downtime. Excessive screen time, particularly involving rapid content consumption like social media feeds, has been associated with diminished attention spans and increased distractibility (Thomann, 2024). Paradoxically, while digital platforms aim to connect individuals, higher screen time has been correlated with feelings of social isolation. It is possibly due to reduced face-to-face interactions (Small et al., 2020).

Global Perspectives on Screen Time and Mental Health

The proliferation of digital devices has led to a significant increase in screen time globally. It has prompted extensive research into its potential effects on mental health. Numerous studies have identified a correlation between excessive screen time and various mental health issues in adults. A systematic review encompassing 32 studies revealed that high screen exposure is associated with increased levels of depression, anxiety, stress, and burnout. Notably, the type of screen activity plays a role. For instance, television viewing has been linked to more negative mental health outcomes compared to computer or mobile device use (Santos et al., 2024).

A meta-analysis focusing on cohort studies found that increased screen time is a predictor of depressive symptoms. The impact varies based on factors such as age, gender, geographic location, and the duration of screen exposure. This suggests that while screen time contributes to depression risk, individual characteristics and contextual factors moderate this relationship (Li et al., 2022).

The nature of the content consumed during screen time significantly influences mental health outcomes. For example, binge-watching television series has been associated with poor diets, increased stress, physical inactivity, and insufficient sleep. All of these can lead to conditions like cardiovascular disease and depression. This behavior shows the complex interplay between content type and psychological well-being (Exelmans & Van Den Bulck, 2017).

It's essential to consider the context in which screen time occurs. During the COVID-19 pandemic, screen time increased significantly. Americans in their twenties used their phones about 28.5 hours a week in 2020, up from 25.9 hours in 2018 (Wagner et al., 2021). This surge was associated with various negative impacts, including psychological issues and health problems like poor sleep and obesity. However, studies suggest that the content viewed matters more than the duration of screen time. It indicates that not all screen time is equally detrimental (Twenge & Farley, 2021).

While many studies highlight the negative impacts of screen time, some researchers argue against a one-size-fits-all perspective. Psychologist Pete Etchells, in his book "Unlocked," critiques studies linking screen time to adverse effects. He pointed out that many studies are based on correlational data, which doesn't imply causation. He suggests that factors such as loneliness could lead to both increased phone usage and poor mental health, challenging the notion that screen time is inherently harmful (Etchells, 2024).

Global research indicates a complex relationship between screen time and mental health. Excessive screen time, particularly involving specific content types, is associated with negative psychological outcomes. However, individual differences and contextual factors also play crucial roles.

Devices and Content Impacts

Smartphones have become ubiquitous in daily life. It offers constant connectivity and access to information. However, excessive smartphone use has been linked to various mental health issues. Problematic smartphone usage is associated with higher levels of depression and anxiety among adults (Subramaniam et al., 2024). Continuous staring at smartphone screens can strain the eyes and disrupt circadian rhythms, leading to poor sleep quality (Daniyal et al., 2022). Frequent smartphone use can impair attention span and productivity, as users are often distracted by notifications and the urge to check their devices (*Is Your Phone Affecting Your Mental Health?*, 2022).

Television viewing remains a popular leisure activity, but excessive consumption has been associated with negative mental health outcomes. Mentally passive activities, such as watching TV, are linked to a 43% increase in the risk of depression *(Watching TV, Passive Sitting, Linked to a 43% Higher Risk of Depression,* 2023). Similarly, excessive gaming is linked to addictive behaviors and may increase aggression and anxiety levels (Dill & Dill, 1998). However, moderate gaming can serve as a stress reliever and provide a sense of achievement (Scott & Shaylee, 2022).

Social media platforms have become integral to daily life. They offer avenues for connection and information sharing. However, excessive and passive use has been linked to negative mental health outcomes. A scoping review found that 78.6% of studies reported associations between heavy social media use and increased depression, anxiety, mood disturbances, and loneliness (Koh et al., 2024). The phenomenon of "Fear of Missing Out" (FOMO) exacerbates these issues, as users constantly compare their lives to curated online portrayals. This leads to decreased self-esteem and heightened anxiety (Hunt et al., 2018). Moreover, the use of beauty filters and photo editing tools on platforms like Instagram and Snapchat has been associated with body image concerns. This has led to terms like "Snapchat Dysmorphia," where individuals seek cosmetic procedures to resemble their filtered images (Eshiet, 2020).

Role of Neuroplasticity

Neuroplasticity refers to the brain's capacity to reorganize its structure, function, and connections in response to experiences, learning, and environmental changes. This dynamic adaptability underpins the brain's ability to recover from injuries, adapt to new learning, and modify behavior patterns. Neuroplastic changes can be both beneficial and detrimental, depending on the nature and duration of the stimuli involved (Kays et al., 2012).

The pervasive use of digital devices has introduced a new dimension to environmental stimuli. Excessive screen time has been associated with alterations in brain structure and function. For example, consistent engagement with fast-paced digital content may reinforce neural circuits associated with quick information processing but might also diminish pathways related to deep focus and critical thinking (Shanmugasundaram & Tamilarasu, 2023). Excessive screen time has been linked to alterations in brain regions responsible for cognitive control and reward processing. It potentially impacts decision-making and emotional regulation (Marciano et al., 2021).

Moreover, the constant stimulation from digital devices can lead to "popcorn brain." It is a term describing the brain's reduced capacity to focus due to overstimulation. This condition reflects the brain's neuroplastic adaptation to rapid, high-intensity stimuli, resulting in diminished attention spans and increased distractibility (Thomann, 2024). The brain's reward pathways may also become desensitized. This means that the brain will require more intense stimuli to achieve the same level of satisfaction, potentially leading to addictive behaviors (Dunckley, 2024).

Excessive screen time has been associated with alterations in brain structure and function. A study from Stanford University indicated that adults aged 18–25 who engaged in high levels of screen use exhibited thinning of the cerebral cortex, the brain region responsible for processing memory and cognitive functions such as decision-making and problem-solving. This cortical thinning may impair learning and memory and increase the risk of early neurodegeneration (Descourouez, 2024). Another study on the associations between recreational time and brain health in middle-aged and older adults indicated that high TV viewing time is associated with increased risk of various brain-related disorders (Xu et al., 2024).

The content consumed during screen time plays a significant role in shaping neuroplastic outcomes. Engagement with violent or fast-paced digital content has been linked to the activation of dopamine and reward pathways. It is speculated to reinforce maladaptive neural patterns associated with attention-deficit/hyperactivity disorder (ADHD) behaviors. Conversely, educational and cognitively demanding content may promote beneficial neural adaptations, enhancing cognitive functions (Lissak, 2018).

Neuroplasticity is a double-edged sword in the context of screen time. The brain's adaptability allows for learning and recovery. However, excessive or inappropriate digital engagement can lead to maladaptive neural changes, adversely affecting psychological health.

Theoretical Framework

This study is grounded in the theoretical understanding that digital media exposure influences psychological well-being and neuroplastic outcomes through both the type of device used and the nature of content consumed. Emerging research suggests that excessive or passive digital media use, particularly through mobile phones and social networking platforms, can lead to adverse psychological outcomes such as emotional exhaustion, anxiety, and reduced subjective well-being (Montag & Walla, 2016; Twenge et al., 2018). These effects are often compounded by algorithmic content delivery that promotes compulsive engagement and diminished cognitive control (Alter, 2018). Building on the neurocognitive framework of environmental stimulation and brain plasticity (Draganski et al., 2004; Green & Bavelier, 2008), the model posits that digital engagement is not a monolithic construct, but a multidimensional behavior that can exert differential effects on mental and neurological health.

The dependent variables in this study are psychological well-being, measured by the WHO-5 Well-being Index (Topp et al., 2015), and two forms of neuroplasticity—adaptive neuroplasticity and maladaptive neuroplasticity. The independent variables include device types (smartphone, laptop/desktop, TV, gaming console) and content types (TV shows/ movies, social media, gaming, work-related task, and educational content).

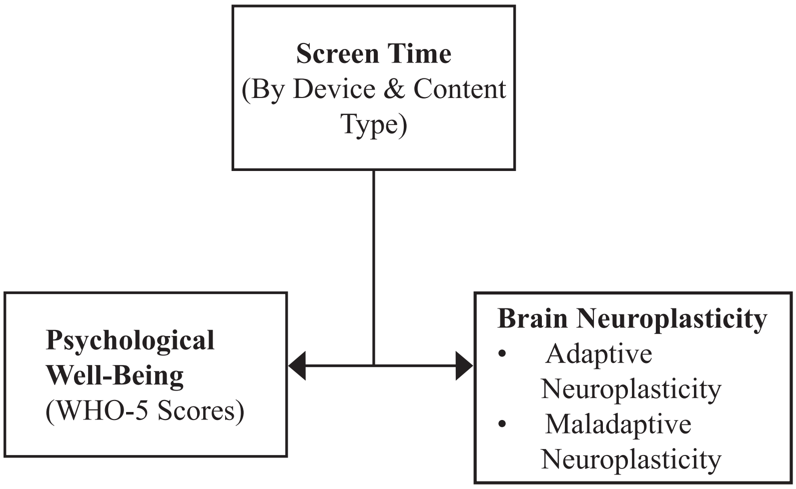

Figure 1. Conceptual diagram of the theoretical framework

Figure 1 presents the conceptual framework of this study. It delineates the hypothesized relationships between various forms of screen time and their impact on well-being and neuroplasticity. The model assumes that not all digital behaviors are inherently beneficial or harmful, but that the impact depends on both device modality and content quality. This theoretical model aligns with recent calls in digital psychology and cognitive neuroscience to move beyond simplistic measures of "screen time" and adopt more nuanced, content-specific analyses (Twenge & Farley, 2021).

Gaps in the Literature

Despite the global proliferation of research examining the relationship between screen time and psychological well-being, significant gaps persist, particularly in Kathmandu, Nepal.

Limited Research on Adult Populations in Nepal

The majority of studies investigating screen time and mental health have predominantly focused on children and adolescents. For instance, research in Bhaktapur assessed screen time among children aged 3–10 years (Shrestha et al., 2022). However, there is a paucity of data concerning adult populations in Nepal. Due to the rapid digitalization of the country, this demographic is increasingly engaged with digital devices, yet their screen time behaviors and associated psychological outcomes remain underexplored.

Lack of Differentiation Between Device Types and Content

Existing literature often treats screen time as a monolithic construct, without distinguishing between different devices (e.g., smartphones, laptops, televisions) or the nature of the content consumed (e.g., social media, educational material, entertainment). This oversimplification overlooks the nuanced effects that specific devices and content types may have on mental health. For example, a study showed the association between internet addiction and poor sleep quality among adults, but did not differentiate between the types of devices or content involved (Arayici et al., 2025).

Insufficient Understanding of Neuroplasticity in Relation to Screen Time

While global studies have begun to explore how excessive screen time may influence neuroplastic changes in the brain, such as cortical thinning and impaired cognitive functions, there is a dearth of research examining these phenomena within the Nepali adult population. Understanding how prolonged screen exposure affects brain structure and function in the Nepali context is crucial for developing targeted mental health interventions.

Addressing these gaps is essential for a comprehensive understanding of how screen time impacts the psychological well-being and brain development of adults in Kathmandu.

Methodology

Research Design

This study employed a quantitative, cross-sectional survey design to assess the relationship between screen time and psychological well-being among adults in Kathmandu, Nepal. The goal was to investigate both the psychological and neurological effects of screen usage by analyzing data collected through standardized instruments and self-report measures.

Population and Sample

The target population consisted of individuals aged 18 years and above who resided in Kathmandu. A total of 369 participants were recruited using a non-probability convenience sampling method, and the responses of 359 participants were taken into consideration after data cleaning. The sample was diverse in age, gender, and occupational background, ensuring a broad representation of screen usage habits.

Data Collection Procedure

Data were collected through an online survey disseminated via Google Forms. The survey link was distributed through social media platforms (e.g., Facebook, WhatsApp) and email to facilitate a wide reach. Participation was voluntary, and informed consent was obtained electronically from all respondents before survey initiation.

Measures

Psychological Well-Being

Psychological well-being was assessed using the World Health Organization's Five Well-Being Index (WHO-5). This validated tool, widely used in psychological research, consists of five items measuring positive emotional states over the past two weeks. Each item is rated on a 6-point scale from 0 (at no time) to 5 (all of the time), yielding a total score ranging from 0 to 25. Higher scores indicate greater well-being. The WHO-5 has demonstrated high internal consistency and cross-cultural applicability (Topp et al., 2015).

Neurological Impact

A 5-point Likert scale was developed to measure perceived neurological impacts of screen use, such as difficulty concentrating, disrupted sleep patterns, mental fatigue, and reduced memory retention. Responses ranged from 1 (strongly disagree) to 5 (strongly agree). These items were constructed based on existing literature concerning the cognitive impacts of screen exposure (Small et al., 2020).

Data Processing and Analysis

The collected data were cleaned to remove incomplete or inconsistent responses. Descriptive statistics (means, frequencies, and standard deviations) were computed to summarize demographic information and screen usage patterns. Inferential statistical techniques, including correlation and multiple regression analysis, were applied to assess the relationships between screen time by device/ content type, psychological well-being scores, and perceived neurological effects. Statistical analyses were conducted using SPSS Version 21.

Ethical Considerations

This study adhered to ethical research practices.

Participation was anonymous, and no personally identifiable information was collected.

Results

The analysis included 359 participants. Of these, 185 were female (51.5%) and 174 were male (48.5%), indicating a nearly equal gender distribution. No participants identified as belonging to the "Other" gender category.

Participants were categorized into five age groups:

Table 1. Age demographics of the participants

Age Group (yrs)	No. of Participants	Percent
18-24	234	65.2
25-34	44	12.3
35-44	51	14.2
45-54	21	5.9
55 and above	9	2.5

The data show that the sample is predominantly composed of young adults, with the 18–24 age group comprising nearly two-thirds of the total respondents.

Table 2. Employment status of the participants

Employment Status	No. of Participants	Percent
Students	211	58.8
Employed	139	38.7
Self-employed	6	1.7
Unemployed	3	0.8

In terms of employment status, the participant pool was largely composed of students, followed by employed individuals.

Rationale for Group Inclusion Threshold

For statistical analysis and group comparisons, only those demographic categories with more than 30 participants were considered. This decision is based on the Central Limit Theorem (CLT), which posits that when the sample size (n) is greater than or equal to 30, the sampling distribution of the mean tends to approximate a normal distribution, regardless of the original distribution of the data (Lumley et al., 2002). This threshold increases the reliability and validity of inferential statistics such as t-tests, ANOVA, and regression models. Including subgroups with fewer than 30 participants can lead to low statistical power, increased standard error, and unreliable parameter estimates. This compromises the generalizability of the findings.

Therefore, in this study, the analytical focus was limited to:

- **Age groups:** 18–24, 25–34, and 35–44
- **Occupational groups:** Students and Employed

This ensures that the statistical comparisons drawn from these groups are meaningful.

Table 3. Descriptive statistics of screentime by device type

Device Type	N	Minimum (hr)	Maximum (hr)	Mean (hr)	Std. Deviation (hr)
Smartphone	359	0.00	19.00	4.02	2.36
Laptop/ Desktop	359	0.00	14.00	3.99	2.84
Television	359	0.00	3.00	0.29	0.61
Gaming Console	359	0.00	5.00	0.14	0.56
Average	-	-	-	8.44	1.88

Table 3 presents the descriptive statistics for daily screen time by device type. On average, participants reported a total daily screen time of 8.44 hours (σ = 1.88) across all devices. Smartphones were the most frequently used device, with a mean daily usage of 4.02 hours (σ = 2.36), followed closely by laptops/ desktops ($\bar{X}$ = 3.99 hours, σ = 2.84). Time spent on televisions ($\bar{X}$ = 0.29 hours, σ = 0.61) and gaming consoles ($\bar{X}$ = 0.14 hours, σ = 0.56) was substantially lower. These findings show the dominant role of mobile and computing devices in daily digital engagement.

Table 4. Descriptive statistics of screentime by content type

Content Type	N	Minimum (hr)	Maximum (hr)	Mean (hr)	Std. Deviation (hr)
TV Shows/ Movies	359	0.00	9.00	1.17	1.33
Social Media	359	0.00	13.00	2.40	1.90
Gaming	359	0.00	8.00	0.40	1.04
Work-Related Tasks	359	0.00	12.00	3.08	2.44
Educational Content	359	0.00	10.00	1.88	1.38

Table 4 summarizes daily screen time by content type. Participants reported spending the most time on work-related tasks ($\bar{X}$ = 3.08 hours, σ = 2.44), followed by social media usage ($\bar{X}$ = 2.40 hours, σ = 1.90). Time spent engaging with educational content was also notable ($\bar{X}$ = 1.88 hours, σ = 1.38), while consumption of TV shows/movies ($\bar{X}$ = 1.17 hours, σ = 1.33) and gaming ($\bar{X}$ = 0.40 hours, σ = 1.04) was relatively lower. These patterns suggest that while entertainment remains a key component of digital behavior, work and learning activities constitute a major share of screen time.

Tables 5 through 10 provide a comprehensive overview of the relationships between screen time across different devices and content types, psychological well-being, and neuroplasticity outcomes. In this study, a p-value of less than 0.05 was considered indicative of statistical significance.

Table 5. Correlation coefficients for the whole sample

Model		Beta	p-Value	R^2
WHO-5 Score	Constant		0.000	0.073
	Smartphone	-0.267	0.000	
	Laptop/ Desktop	0.006	0.915	
	Television	0.050	0.342	
	Gaming Console	0.006	0.912	
WHO-5 Score	Constant		0.000	0.094
	TV Shows/ Movies	-0.092	0.078	
	Social Media	-0.244	0.000	
	Gaming	0.015	0.761	
	Work-Related Tasks	0.118	0.021	
	Educational Content	0.003	0.957	
Maladaptive Neuroplasticity Score	Constant		0.000	0.121
	Smartphone	0.342	0.000	
	Laptop/ Desktop	-0.023	0.650	
	Television	0.019	0.709	
	Gaming Console	0.029	0.568	

Adaptive Neuroplasticity Score	Constant		0.000	0.047
	Smartphone	-0.211	0.000	
	Laptop/ Desktop	0.008	0.878	
	Television	-0.036	0.498	
	Gaming Console	-0.014	0.785	
Maladaptive Neuroplasticity Score	Constant		0.000	0.209
	TV Shows/ Movies	0.098	0.046	
	Social Media	0.411	0.000	
	Gaming	0.001	0.986	
	Work-Related Tasks	-0.098	0.040	
	Educational Content	-0.001	0.990	
Adaptive Neuroplasticity Score	Constant		0.000	0.127
	TV Shows/ Movies	-0.107	0.037	
	Social Media	-0.212	0.000	
	Gaming	0.103	0.039	
	Work-Related Tasks	0.052	0.297	
	Educational Content	0.215	0.000	

In the overall sample, smartphone usage showed a weak negative correlation with WHO-5 psychological well-being scores ($\beta = -0.267$, $p < 0.05$). This negative beta coefficient indicates that for every one-hour increase in smartphone use, there is a decrease in WHO-5 scores by 0.267 units. This suggests that higher smartphone use predicts lower levels of psychological well-being. No other devices (laptops/desktops, televisions, or gaming consoles) showed significant predictive effects on well-being in the overall sample.

Content type exerted a more pronounced influence than device type. Specifically, social media usage had a weak negative correlation with psychological well-being ($\beta = -0.244$, $p < 0.05$. In contrast, work-related digital engagement had a weak positive correlation with WHO-5 scores ($\beta = 0.118$, $p < 0.05$), indicating that such usage may enhance mental well-being.

This study conceptualized maladaptive neuroplasticity as brain changes resulting from unhealthy digital behavior patterns, such as attention fragmentation, emotional dysregulation, or compulsive use. Conversely, adaptive neuroplasticity scores reflect positive, growth-oriented changes, such as cognitive flexibility, learning, and memory enhancement, which are promoted by constructive digital engagement. It indicates the brain's ability to rewire and strengthen itself in ways that build overall mental acuity in response to healthy and purposeful screen use patterns.

Smartphone usage had a weak positive correlation with maladaptive neuroplasticity ($\beta = 0.342$, $p < 0.05$) and a weak negative correlation with adaptive neuroplasticity ($\beta = -0.211$, $p < 0.05$). This suggests that excessive smartphone use may promote harmful brain adaptations while simultaneously impairing beneficial ones. These maladaptive outcomes testify to how specific patterns of digital interaction can negatively reshape neural pathways, leading to cognitive and emotional vulnerabilities. No other device showed significant associations.

Among the content types, social media use had a moderate positive association with maladaptive neuroplasticity ($\beta = 0.411$, $p < 0.05$) and a weak negative correlation with adaptive neuroplasticity ($\beta = -0.212$, $p < 0.05$). This indicates that habitual social media use may reshape the brain in maladaptive ways while diminishing its ability to grow and learn. On the other hand, educational content had a weak positive correlation with adaptive neuroplasticity ($\beta = 0.215$, $p < 0.05$), and work-related content had a weak negative correlation with maladaptive neuroplasticity ($\beta = -0.098$, $p < 0.05$). It showed that structured, goal-directed engagement has neuroprotective and developmental benefits. Gaming also had a weak positive correlation with adaptive neuroplasticity ($\beta = 0.103$, $p < 0.05$). Watching TV shows/ movies had a weak positive correlation with maladaptive neuroplasticity ($\beta = 0.098$, $p < 0.05$) and a weak negative correlation with adaptive neuroplasticity ($\beta = -0.107$, $p < 0.05$). This indicates that passive screen use may impair the brain's positive plastic responses while developing unproductive ones.

Table 6. Correlation coefficients for 18 - 24 age group

Model		Beta	p-Value	R^2
WHO-5 Score	Constant		0.000	0.020
	Smartphone	-0.109	0.104	
	Laptop/ Desktop	0.072	0.300	
	Television	0.043	0.523	
	Gaming Console	-0.017	0.797	
WHO-5 Score	Constant		0.000	0.050
	TV Shows/ Movies	-0.037	0.568	
	Social Media	-0.173	0.009	
	Gaming	0.075	0.250	
	Work-Related Tasks	0.078	0.233	
	Educational Content	0.026	0.689	
Maladaptive Neuroplasticity Score	Constant		0.000	0.072
	Smartphone	0.265	0.000	
	Laptop/ Desktop	0.044	0.509	
	Television	0.046	0.484	
	Gaming Console	0.035	0.586	
Adaptive Neuroplasticity Score	Constant		0.000	0.033
	Smartphone	-0.127	0.058	
	Laptop/ Desktop	0.081	0.239	
	Television	-0.051	0.448	
	Gaming Console	-0.038	0.560	
Maladaptive Neuroplasticity Score	Constant		0.000	0.177
	TV Shows/ Movies	0.109	0.074	
	Social Media	0.383	0.000	
	Gaming	-0.008	0.889	
	Work-Related Tasks	-0.044	0.472	
	Educational Content	-0.040	0.508	
Adaptive Neuroplasticity Score	Constant		0.000	0.138
	TV Shows/ Movies	-0.053	0.390	
	Social Media	-0.179	0.004	
	Gaming	0.166	0.008	
	Work-Related Tasks	0.043	0.489	
	Educational Content	0.245	0.000	

Among the 18–24 age group, no specific device usage was significantly correlated with WHO-5 scores. This suggests that device type may not independently predict well-being in this demographic. However, social media use exhibited a weak negative correlation with psychological well-being ($\beta = -0.173$, $p < 0.05$), reflecting possible emotional exhaustion or social comparison effects. Other content types were not significant predictors in this group.

Smartphone usage showed a weak positive correlation with maladaptive neuroplasticity ($\beta = 0.265$, $p < 0.05$), but had no significant correlation with adaptive neuroplasticity. This implies that younger individuals are particularly vulnerable to brain strain linked to high-frequency smartphone use. Social media use had a weak positive correlation with maladaptive neuroplasticity ($\beta = 0.383$, $p < 0.05$). In contrast, educational content ($\beta = 0.245$, $p < 0.05$) and gaming ($\beta = 0.166$, $p < 0.05$) showed weak positive correlation with adaptive neuroplasticity. This showed their potential as a cognitive tool in younger populations.

Table 7. Correlation coefficients for 25 - 34 age group

Model		Beta	p-Value	R^2
WHO-5 Score	Constant		0.000	0.179
	Smartphone	-0.420	0.010	
	Laptop/ Desktop	0.059	0.697	
	Television	-0.069	0.646	
	Gaming Console	0.117	0.460	
WHO-5 Score	Constant		0.000	0.220
	TV Shows/ Movies	-0.130	0.422	
	Social Media	-0.327	0.049	
	Gaming	-0.061	0.688	
	Work-Related Tasks	0.206	0.179	
	Educational Content	-0.167	0.271	
Maladaptive Neuroplasticity Score	Constant		0.000	0.351
	Smartphone	0.448	0.002	
	Laptop/ Desktop	-0.229	0.095	
	Television	0.214	0.115	
	Gaming Console	0.019	0.892	
Adaptive Neuroplasticity Score	Constant		0.000	0.013
	Smartphone	-0.055	0.749	
	Laptop/ Desktop	0.043	0.796	
	Television	0.049	0.767	
	Gaming Console	-0.077	0.657	
Maladaptive Neuroplasticity Score	Constant		0.000	0.365
	TV Shows/ Movies	0.164	0.262	
	Social Media	0.412	0.007	
	Gaming	-0.007	0.960	
	Work-Related Tasks	-0.303	0.031	
	Educational Content	-0.141	0.302	

Adaptive Neuroplasticity Score	Constant		0.000	0.091
	TV Shows/ Movies	-0.095	0.584	
	Social Media	-0.094	0.591	
	Gaming	-0.181	0.271	
	Work-Related Tasks	0.173	0.293	
	Educational Content	-0.033	0.838	

In the 25–34 age group, smartphone use showed a moderate negative correlation with psychological well-being (β = -0.420, $p < 0.05$), indicating more pronounced effects of digital engagement on this age group's mental health. Social media use also showed a weak negative correlation with psychological well-being (β = -0.327, $p < 0.05$), suggesting consistent emotional strain across content types. Work-related digital use did not show a statistically significant correlation with well-being in this group.

Smartphone use exhibited a moderate positive correlation with maladaptive neuroplasticity (β = 0.448, $p < 0.05$), reinforcing the cognitive costs of habitual mobile usage in early adulthood. Similarly, social media use showed a moderate positive correlation with maladaptive neuroplasticity (β = 0.412, $p < 0.05$), while work-related content showed a weak negative correlation with maladaptive neuroplasticity (β = -0.303, $p < 0.05$). Productivity-oriented digital use may be neurologically beneficial in this group.

Table 8. Correlation coefficients for 35 - 44 age group

Model		Beta	p-Value	R^2
WHO-5 Score	Constant		0.000	0.045
	Smartphone	-0.161	0.287	
	Laptop/ Desktop	0.067	0.664	
	Television	0.127	0.386	
	Gaming Console	0.091	0.550	
WHO-5 Score	Constant		0.000	0.078
	TV Shows/ Movies	-0.022	0.881	
	Social Media	-0.189	0.252	
	Gaming	0.131	0.439	
	Work-Related Tasks	0.181	0.276	
	Educational Content	0.135	0.391	
Maladaptive Neuroplasticity Score	Constant		0.000	0.185
	Smartphone	0.435	0.003	
	Laptop/ Desktop	-0.151	0.293	
	Television	-0.128	0.347	
	Gaming Console	-0.014	0.918	
Adaptive Neuroplasticity Score	Constant		0.000	0.161
	Smartphone	0.366	0.012	
	Laptop/ Desktop	-0.259	0.079	
	Television	-0.043	0.756	
	Gaming Console	0.095	0.505	

Maladaptive Neuroplasticity Score	Constant		0.000	0.224
	TV Shows/ Movies	0.086	0.519	
	Social Media	0.448	0.004	
	Gaming	-0.069	0.657	
	Work-Related Tasks	-0.210	0.171	
	Educational Content	0.156	0.281	
Adaptive Neuroplasticity Score	Constant		0.000	0.221
	TV Shows/ Movies	0.009	0.948	
	Social Media	0.299	0.052	
	Gaming	0.007	0.967	
	Work-Related Tasks	-0.170	0.268	
	Educational Content	0.346	0.020	

Device usage and content type did not significantly correlate with WHO-5 scores for the 35–44 age group. This possibly indicates a greater digital literacy or selective content engagement within this demographic.

Smartphone use exhibited a moderate positive correlation with maladaptive neuroplasticity ($\beta = 0.435$, $p < 0.05$) and a weak positive correlation with adaptive neuroplasticity ($\beta = 0.366$, $p < 0.05$). This suggests a dual effect: while excessive use may lead to cognitive strain, smartphone engagement in certain contexts (e.g., productivity, learning) may also enhance neurocognitive development.

Social media use showed a moderate positive correlation with maladaptive neuroplasticity ($\beta = 0.448$, $p < 0.05$), while educational content showed a weak positive correlation with adaptive neuroplasticity ($\beta = 0.346$, $p < 0.05$). This pattern suggests that passive, overstimulating content may impair brain health, while structured and intellectually engaging content can promote cognitive growth across age groups.

Table 9. Correlation coefficients for students

Model		Beta	p-Value	R^2
WHO-5 Score	Constant		0.000	0.017
	Smartphone	-0.113	0.111	
	Laptop/ Desktop	0.034	0.640	
	Television	0.015	0.836	
	Gaming Console	0.037	0.598	
WHO-5 Score	Constant		0.000	0.051
	TV Shows/ Movies	-0.047	0.494	
	Social Media	-0.189	0.007	
	Gaming	0.062	0.367	
	Work-Related Tasks	0.046	0.505	
	Educational Content	0.027	0.694	
Maladaptive Neuroplasticity Score	Constant		0.000	0.056
	Smartphone	0.238	0.001	
	Laptop/ Desktop	0.039	0.580	
	Television	0.013	0.851	
	Gaming Console	0.032	0.638	

Adaptive Neuroplasticity Score	Constant		0.000	0.034
	Smartphone	-0.140	0.047	
	Laptop/ Desktop	0.074	0.303	
	Television	-0.044	0.527	
	Gaming Console	-0.030	0.661	
Maladaptive Neuroplasticity Score	Constant		0.000	0.194
	TV Shows/ Movies	0.133	0.038	
	Social Media	0.363	0.000	
	Gaming	-0.064	0.315	
	Work-Related Tasks	-0.089	0.162	
	Educational Content	-0.084	0.183	
Adaptive Neuroplasticity Score	Constant		0.000	0.155
	TV Shows/ Movies	-0.050	0.446	
	Social Media	-0.180	0.007	
	Gaming	0.158	0.015	
	Work-Related Tasks	0.032	0.617	
	Educational Content	0.279	0.000	

Device usage did not show a significant correlation with WHO-5 psychological well-being scores among students. Among content types, social media use demonstrated a weak negative correlation with well-being ($\beta = -0.189$, $p < 0.05$). Educational or gaming content showed no significant correlation in this group.

Smartphone use had a weak positive correlation with maladaptive neuroplasticity ($\beta = 0.238$, $p < 0.05$) and a weak negative correlation with adaptive neuroplasticity ($\beta = -0.140$, $p < 0.05$). This indicates that excessive mobile phone use may hinder students' cognitive development. Social media use showed a weak positive correlation with maladaptive neuroplasticity ($\beta = 0.363$, $p < 0.05$), reinforcing its negative neurological impact. In contrast, educational content ($\beta = 0.279$, $p < 0.05$) and gaming ($\beta = 0.158$, $p < 0.05$) had a weak positive correlation with adaptive neuroplasticity. They may have a potential to assist in cognitive growth. Additionally, watching TV shows/ movies was weakly positively correlated with maladaptive neuroplasticity ($\beta = 0.133$, $p < 0.05$). This indicates possible overstimulation effects from passive media consumption.

Table 10. Correlation coefficients for employed

Model		Beta	p-Value	R^2
WHO-5 Score	Constant		0.000	0.031
	Smartphone	-0.167	0.062	
	Laptop/ Desktop	-0.052	0.556	
	Television	0.011	0.899	
	Gaming Console	0.041	0.637	
WHO-5 Score	Constant		0.000	0.049
	TV Shows/ Movies	-0.058	0.500	
	Social Media	-0.196	0.036	
	Gaming	0.149	0.104	
	Work-Related Tasks	0.114	0.199	
	Educational Content	-0.004	0.965	

Maladaptive Neuroplasticity Score	Constant		0.000	0.252
	Smartphone	0.495	0.000	
	Laptop/ Desktop	-0.188	0.017	
	Television	0.022	0.775	
	Gaming Console	-0.041	0.595	
Adaptive Neuroplasticity Score	Constant		0.000	0.037
	Smartphone	0.002	0.986	
	Laptop/ Desktop	-0.168	0.059	
	Television	-0.129	0.143	
	Gaming Console	-0.011	0.899	
Maladaptive Neuroplasticity Score	Constant		0.000	0.254
	TV Shows/ Movies	0.009	0.904	
	Social Media	0.470	0.000	
	Gaming	0.075	0.353	
	Work-Related Tasks	-0.195	0.014	
	Educational Content	0.149	0.052	
Adaptive Neuroplasticity Score	Constant		0.000	0.040
	TV Shows/ Movies	-0.115	0.184	
	Social Media	-0.062	0.503	
	Gaming	0.089	0.331	
	Work-Related Tasks	-0.035	0.698	
	Educational Content	0.156	0.071	

Device usage did not significantly correlate with WHO-5 psychological well-being scores among employed individuals. Social media use showed a weak negative correlation with psychological well-being ($\beta = -0.196$, $p < 0.05$). This suggests a consistent pattern of psychological strain from passive or compulsive engagement. Other content types did not show significant correlations with WHO-5 score.

Smartphone use showed a moderate positive correlation with maladaptive neuroplasticity ($\beta = 0.495$, $p < 0.05$). On the other hand, laptop/desktop use had a weak negative correlation with maladaptive neuroplasticity ($\beta = -0.188$, $p < 0.05$). Professional digital tools may be less neurologically disruptive. Social media use had a moderate positive correlation with maladaptive neuroplasticity ($\beta = 0.470$, $p < 0.05$), while work-related tasks had a weak negative correlation with maladaptive neuroplasticity ($\beta = -0.195$, $p < 0.05$). These results emphasize the need for intentional and mindful digital engagement in professional settings.

In this study, the coefficient of determination (R^2) values ranged from 0.013 to 0.365, indicating a low to moderate proportion of variance explained by the models. In behavioral and psychological research, it is common to observe relatively low R^2 values because human behavior is influenced by a wide range of unmeasured factors (Ozili, 2022). Psychological well-being and neuroplasticity are influenced by a complex interplay of biological, environmental, social, and psychological factors beyond digital engagement alone.

Notably, the linear regression models computed in SPSS returned a constant value of zero, implying a regression through the origin. However, this statistical output should not be interpreted to mean that individuals with no digital engagement will necessarily have high psychological well-being or exhibit specific neuroplasticity outcomes. Instead, it reflects the limitations of the model structure and variable scope, and underscores the fact that digital behavior is just one of many contributors to psychological and neural outcomes. Thus, while the explanatory power of the models is modest, the statistically significant relationships identified in this study still offer meaningful insight into how different types of screen time interact with well-being and brain development.

Discussion

This study reveals significant and nuanced relationships between screen use, psychological well-being, and brain neuroplasticity across Kathmandu's age and occupational groups. The effects of device type and content type differ in both degree and direction. It offers critical insights into how digital behaviors shape mental health and brain development.

Digital Devices and Well-being

Smartphone use consistently emerged as the most impactful device across psychological and neurological dimensions. Among the overall sample, increased smartphone usage was linked to both lower psychological well-being and higher maladaptive neuroplasticity, while suppressing adaptive neural development. This suggests that excessive mobile device engagement—often marked by interruptions, passive scrolling, and compulsive checking—can degrade mental health and hinder healthy brain adaptation.

The 25–34 age group showed the strongest negative relationship between smartphone use and well-being. It points out a vulnerable phase where career pressures, social comparisons, and digital overload converge. In contrast, the 18–24 group did not show significant associations with well-being by device, suggesting greater digital normalization or resilience, though their brains still showed signs of maladaptive change. Interestingly, the 35–44 group exhibited both maladaptive and adaptive neuroplasticity linked to smartphone use. It suggests a dual effect where digital tools can either harm or stimulate, depending on the context (e.g., productivity vs. overuse).

Device impact was also sensitive to employment status. Among students, smartphone use impaired adaptive neuroplasticity. It implies a detrimental effect on learning, memory, and focus. For the employed, smartphones induced maladaptive neuroplasticity, while laptops/desktops were related with reduced harm. It indicates that structured, goal-oriented device use in work settings may be less neurologically disruptive.

Content Type and Brain-Behavior Dynamics

Content engagement proved more influential than device type in predicting well-being and neuroplasticity outcomes. Across all groups, social media use was consistently and relatively strongly associated with reduced psychological well-being and heightened maladaptive neuroplasticity. These findings echo existing research indicating that social media encourages emotional dysregulation, fragmented attention, and negative social comparison (Montag & Walla, 2016; Twenge & Campbell, 2018). Moreover, the more social media usage less is the amygdala volumes in the brain, ultimately affecting brain structure (He et al., 2017).

In contrast, educational and work-related content showed positive or protective effects. Educational content boosted adaptive neuroplasticity, especially in the 18–24 and 35–44 age groups. It suggests that intellectually stimulating content promotes cognitive growth and learning. Work-related digital engagement correlated positively with psychological well-being in the overall sample. It protected against maladaptive neural change in older adults and professionals, affirming the benefits of goal-directed, purposeful digital use.

Gaming offered a surprising benefit. While often stigmatized, it positively predicted adaptive neuroplasticity in younger users and students. This supports emerging research on "serious games" and their ability to enhance spatial reasoning, problem-solving, and memory (Granic et al., 2014). It is similar to how chess causes adaptive plasticity — the brain reshapes itself to become more specialized, efficient, and automated for chess-related skills (Hänggi et al., 2014). However, TV shows and movies, particularly passive consumption, were correlated with mild increases in maladaptive neuroplasticity, hinting the difference between active vs. passive engagement.

Age and Role-Specific Implications

Younger individuals (18–24) showed apparent neurological vulnerability to smartphones and social media, even if their well-being scores were not significantly impacted by device type. This may reflect a delayed or subconscious cognitive cost. Early adulthood (25–34) appeared most affected overall, psychologically and neurologically, by digital overuse. It is so possibly due to transitional life stressors and high digital immersion.

Students, as a group, showed a particularly concerning profile. Digital engagement eroded well-being and supported maladaptive neuroplasticity while impeding beneficial brain changes. In contrast, employed individuals experienced some protective effects from structured digital engagement (e.g., via work tools), though social media remained a significant threat to brain health and well-being.

Conclusion

This study demonstrates that digital engagement patterns significantly influence psychological well-being and brain neuroplasticity. Excessive smartphone use and social media consumption were consistently associated with lower well-being and increased maladaptive neuroplasticity across demographic groups, whereas work-related and educational content were linked to adaptive neuroplastic outcomes. These findings show that the quality and purpose of digital activities, rather than mere screen time, are critical determinants of mental health and cognitive development. Promoting intentional, goal-directed digital behaviors may serve as a protective strategy against the adverse effects of pervasive screen exposure.

Limitation

This study has a few notable limitations that should be acknowledged. First, the research was conducted exclusively in Kathmandu, which may limit the generalizability of the findings to other regions of Nepal. This is problematic particularly for rural areas where digital engagement patterns and socio-cultural factors may differ significantly. Additionally, a significant proportion of the participants belonged to the 18–24 age group and were primarily students. This demographic concentration may introduce bias and limit the applicability of the results to other age groups or occupational categories.

Another methodological limitation lies in the regression models used in the analysis. The constant (intercept) value in the linear regression equations was zero, as produced by SPSS. While this approach simplifies the model, it also assumes that when all independent variables are zero (i.e., no digital engagement), the predicted psychological well-being and neuroplasticity outcomes would also be zero. This assumption is theoretically and practically problematic. Psychological well-being and neuroplasticity are influenced by numerous other factors beyond digital engagement, such as social relationships, physical health, genetics, education, and life experiences. Hence, this modeling limitation points the fact that the regression models do not fully capture the complexity of these psychological constructs.

Future studies should address these limitations by employing more representative and stratified sampling across diverse age groups, regions, and occupations. Additionally, incorporating a broader range of psychological and contextual variables could enhance model accuracy and deepen understanding of the multifaceted nature of psychological well-being and brain plasticity in the digital age.

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