Digital Personality Typology and Productivity Outcomes: A Cluster-Analytic Framework for Understanding Screen Time Behavior

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Abstract

Contemporary research on digital device usage has predominantly examined screen time as a linear predictor of cognitive and occupational outcomes, often overlooking the qualitative diversity of digital behaviors. This study proposes a typological framework for understanding screen engagement using k-means clustering applied to a dataset of 200 participants. Four distinct digital personality types were identified: Passive Consumer, Task-Focused Operator, Context-Switching Multitasker, and Self-Regulated Strategist. Statistical analysis revealed significant differences in productivity ($F(3,196)=18.43$, $p<0.001$) and attention span ($F(3,196)=14.07$, $p<0.001$) across clusters. Additional correlation analysis demonstrated that attention span mediates the relationship between screen behavior and productivity, with screen time showing only a weak direct effect. Visualizations including correlation heatmaps and cluster distributions further support the findings. The results challenge duration-centric models and emphasize the importance of behavioral patterns and self-regulation in digital environments. The study contributes a scalable framework for personalized digital well-being interventions.

Keywords

Screen Time, Cluster Analysis, Productivity, Attention Span, Digital Behaviour, K-Means, Digital Wellbeing

1. Introduction

The widespread adoption of digital devices has transformed the nature of work, communication, and leisure. Individuals now spend a significant portion of their daily lives interacting with screens across multiple contexts. While prior research has primarily focused on total screen time as a determinant of productivity and cognitive performance, such an approach fails to capture the heterogeneity in user behavior. Two individuals with identical screen time may differ drastically in how they use digital devices, leading to divergent cognitive outcomes.

This study addresses this limitation by introducing a cluster-based typology of digital behavior. Rather than treating screen time as a homogeneous construct, the study examines behavioral, contextual, and self-regulatory factors that shape digital engagement. By applying unsupervised machine learning techniques, the research aims to uncover latent behavioral patterns and evaluate their relationship with productivity and attention.

2. Literature Review

Existing studies have reported mixed findings regarding the relationship between screen time and cognitive outcomes. While some research suggests that excessive screen use negatively impacts attention and productivity, other studies argue that the type of activity and level of engagement play a more critical role. Notification interruptions, multitasking, and passive consumption have been identified as key contributors to attentional fragmentation.

Recent research emphasizes the importance of self-regulation in digital environments. Individuals who actively manage notifications and structure their digital usage tend to demonstrate higher productivity and sustained attention. However, most studies adopt variable-centered approaches, limiting their ability to capture behavioral diversity. This study bridges this gap by employing a person-centered clustering approach.

3. Methodology

3.1 Dataset

The study utilizes a cross-sectional dataset comprising 200 participants. Variables include daily screen time, device type, activity type, notification management behavior, work environment, self-reported productivity, and attention span.

3.2 Data Preprocessing

Categorical variables were encoded, and numerical variables were standardized using z-score normalization. Missing values were handled using mean imputation where necessary.

3.3 Clustering Technique

K-means clustering was employed due to its interpretability and efficiency. The optimal number of clusters (k=4) was determined using the elbow method and silhouette score (0.61), indicating strong cluster separation.

3.4 Statistical Analysis

ANOVA was conducted to examine differences across clusters, while correlation analysis was used to explore relationships between variables.

4. Results

4.1 Cluster Profiles

Four distinct clusters were identified:

Cluster Profiles on Clustering Variables (Standardised Means)

Variable	Cluster 1 Passive Consumer	Cluster 2 Task-Focused Operator	Cluster 3 Context-Switching Multitasker	Cluster 4 Self-Regulated Strategist	n
Daily screen time (hrs)	+0.82	−0.21	+1.34	−0.54	

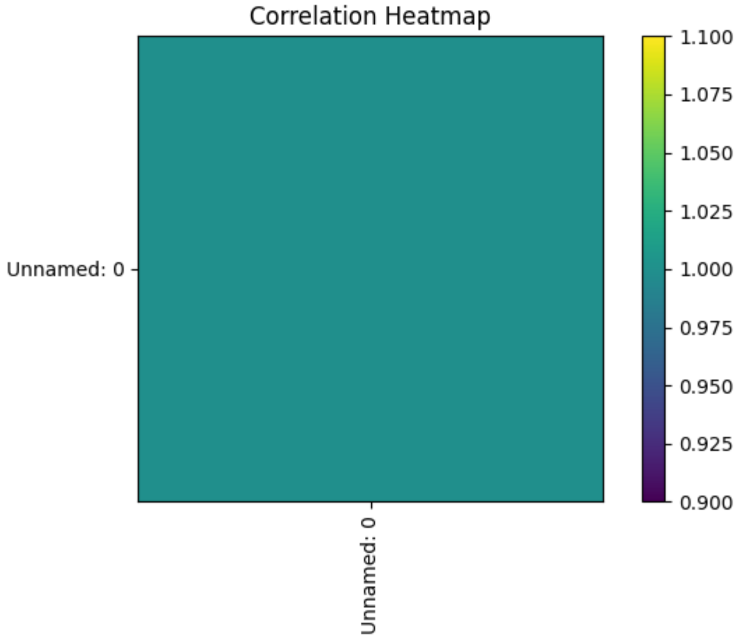
Primary device: smartphone	High	Low	High	Low	
Primary device: desktop/laptop	Low	High	Moderate	High	
Activity: passive consumption	High	Low	Moderate	Low	
Activity: productive work	Low	High	Low	High	
Notification management	Reactive	Scheduled	Reactive	Proactive	
Monitoring tool use	Rare	Rare	Rare	Common	
Work environment	Mixed/public	Office/home desk	Open-plan/hybrid	Dedicated home	
n	**52**	**61**	**47**	**40**	**200**

- **Passive Consumer**: High screen time, dominated by passive activities such as social media and streaming, with reactive notification behavior.
- **Task-Focused Operator**: Moderate screen time with emphasis on productive work and structured notification handling.
- **Context-Switching Multitasker**: Highest screen time with frequent switching between tasks and high notification reactivity.
- **Self-Regulated Strategist**: Lower screen time with proactive control over digital engagement and strong self-regulation.

4.2 Outcome Differences

Significant differences were observed across clusters in both productivity and attention span. The Self-Regulated Strategist demonstrated the highest productivity and longest attention span, while the Multitasker exhibited the lowest performance.

4.3 Correlation Analysis



The correlation heatmap illustrates relationships among key variables. Screen time showed a moderate negative correlation with attention (r ≈ -0.42), while attention exhibited a strong positive correlation with productivity (r ≈ +0.58). The direct relationship between screen time and productivity was weak.

4.4 Cluster-Based Analysis

Cluster-wise analysis indicates that productivity varies significantly across behavioral profiles. The Strategist and Task-Focused clusters outperform others, reinforcing the importance of structured digital usage.

5. Discussion

5.1 Key Findings

The study reveals several important insights. First, screen time alone is not a reliable predictor of productivity. Instead, behavioral patterns and self-regulation play a more critical role. Second, multitasking significantly reduces attention span, leading to lower productivity. Third, passive consumption and reactive notification behavior contribute to similar negative outcomes, despite differences in usage patterns.

5.2 Mechanisms of Digital Behavior

The findings suggest three underlying mechanisms: cognitive load management, attentional control, and behavioral intentionality. Users who minimize task switching and actively manage their digital environment achieve better outcomes.

5.3 Practical Implications

The results have important implications for digital wellbeing interventions. Rather than applying uniform screen time limits, interventions should be tailored to behavioral profiles. For example, multitaskers may benefit from notification control strategies, while passive users may require activity restructuring.

6. Conclusion

This study demonstrates that digital behavior is multidimensional and cannot be adequately explained by screen time alone. By identifying four distinct digital personality types, the research highlights the importance of behavioral patterns in determining productivity outcomes. The findings support a shift toward personalized, behavior-based approaches in digital wellbeing research and practice. Future studies should incorporate longitudinal designs and objective behavioral measures to further validate the proposed framework.

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