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Identifying Digital Behavior Profiles via Usage Patterns, Reward Sensitivity, and Social Reinforcement with Machine Learning Analysis

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ABSTRACT

Objective: The present study aimed to identify and classify distinct digital behavior profiles based on usage patterns, reward sensitivity, and social reinforcement using machine learning techniques.

Methods and Materials: This study employed a cross-sectional, correlational design with an embedded machine learning approach. A total of 412 adult participants from Canada were recruited through stratified online sampling. Data were collected using standardized self-report instruments assessing digital usage patterns, Behavioral Activation System (BAS) components for reward sensitivity, and a social reinforcement scale adapted for online environments. After preprocessing, including normalization and missing data handling, descriptive statistics and correlation analyses were conducted. Unsupervised machine learning techniques, specifically K-means and hierarchical clustering, were applied to identify latent behavioral profiles, with optimal cluster selection based on silhouette coefficients and Davies–Bouldin index values. Principal component analysis (PCA) was used for dimensionality reduction and visualization. Additionally, supervised learning models, including random forest and support vector machine algorithms, were implemented to evaluate the predictive accuracy of cluster membership.

Findings: The analysis revealed a three-cluster solution representing distinct digital behavior profiles: Low Engagement, Balanced Users, and High Reinforcement Seekers. Significant differences were observed across clusters in terms of screen time, multitasking behavior, reward sensitivity, and social reinforcement indicators, with the High Reinforcement Seekers cluster demonstrating the highest levels across all variables. The clustering structure showed strong separation and internal consistency, as confirmed by PCA visualization. Supervised classification models achieved high predictive performance, with the random forest model demonstrating superior accuracy, precision, recall, and F1-score compared to the support vector machine model, indicating robust classification of behavioral profiles based on the selected features.

Conclusion: The findings highlight the multidimensional nature of digital behavior and demonstrate the effectiveness of machine learning techniques in identifying meaningful behavioral profiles. The results underscore the importance of integrating psychological constructs such as reward sensitivity and social reinforcement with behavioral data to better understand digital engagement patterns. This approach provides a foundation for developing targeted interventions and personalized digital well-being strategies, particularly for individuals at risk of excessive or maladaptive digital use.

Keywords: *Digital behavior profiles, machine learning, reward sensitivity, social reinforcement, digital engagement, clustering analysis, behavioral segmentation*

1 Introduction

The rapid proliferation of digital technologies over the past two decades has fundamentally transformed patterns of human behavior, communication, and cognition. Digital environments, particularly social media platforms, online gaming ecosystems, and streaming services, have become deeply embedded in daily life, shaping not only how individuals interact with information but also how they regulate emotions, construct identity, and engage socially. While early research emphasized the benefits of digital connectivity and information accessibility, contemporary scholarship increasingly highlights the complexity and ambivalence of digital engagement, particularly in relation to behavioral reinforcement, psychological well-being, and emerging forms of technology-mediated dependency (Shannon et al., 2025; Xu et al., 2025). In this context, understanding digital behavior is no longer limited to measuring usage duration; instead, it requires a multidimensional perspective that integrates psychological traits, motivational dynamics, and social interaction patterns.

A growing body of evidence suggests that digital behavior is shaped by underlying reinforcement mechanisms that parallel classical conditioning and reward-based learning processes. Social media platforms, for instance, are deliberately designed to provide intermittent rewards—such as likes, comments, and notifications—that activate dopaminergic pathways associated with pleasure and motivation (Lakhan, 2025; Wang & Shen, 2025). These reinforcement loops not only sustain engagement but may also contribute to maladaptive usage patterns when individuals become increasingly reliant on external validation. The concept of reward sensitivity, rooted in behavioral neuroscience, provides a critical lens for understanding why certain individuals are more susceptible to these reinforcement cycles. Individuals with higher reward sensitivity tend to exhibit stronger motivational responses to positive stimuli, thereby increasing their likelihood of prolonged and repetitive engagement with digital platforms (Robayo-Pinzon et al., 2023; Wegmann et al., 2025).

In parallel, social reinforcement has emerged as a central determinant of digital behavior. Unlike traditional forms of reinforcement, which often occur in physical or institutional settings, digital reinforcement is immediate, quantifiable, and socially visible. The number of likes, shares, or comments received on a post serves as a proxy for social approval, thereby influencing self-perception and behavioral repetition. Research indicates that peer dynamics and perceived social norms play a significant role in shaping online engagement, particularly among younger populations (Nguyen et al., 2024; Véronneau & Schwartz-Mette, 2021). Moreover, concerns related to peer evaluation and privacy further complicate these dynamics, as users navigate the tension between self-expression and social acceptance in digitally mediated environments (Nguyen et al., 2024). These findings underscore the importance of integrating social reinforcement constructs into models of digital behavior.

Beyond individual-level factors, the design architecture of digital platforms plays a pivotal role in shaping user behavior. Persuasive design techniques—such as infinite scrolling, personalized content feeds, and algorithmically curated notifications—are engineered to maximize user engagement by leveraging cognitive biases and attentional vulnerabilities (Cemiloglu et al., 2021; Flayelle et al., 2023). These design features blur the boundary between voluntary engagement and behavioral compulsion, raising concerns about the ethical implications of digital technology design. Recent taxonomies of technology design features highlight how specific interface elements can systematically promote habitual or even addictive usage patterns, particularly when combined with reward-based reinforcement mechanisms (Flayelle et al., 2023). Such insights point to the need for analytical frameworks that account for both user characteristics and system-level influences.

The increasing recognition of problematic digital use has led to a surge in research examining its psychological and behavioral correlates. Studies have linked excessive digital engagement to a range of adverse outcomes, including reduced attention span, emotional dysregulation, and symptoms analogous to substance use disorders (Duresso, 2021; Sherlin et al., 2024). Notably, the concept of digital addiction has gained traction as a framework for understanding compulsive online behaviors, with parallels drawn between substance-based and technology-based dependencies (Amirthalingam & Khera, 2024). Emerging research further suggests that digital environments may induce neuroadaptive changes, contributing to phenomena such as digital anhedonia, where individuals experience diminished pleasure from offline activities due to overstimulation from digital rewards (Lakhan, 2025). These developments highlight the urgency of identifying distinct behavioral patterns that may signal vulnerability to problematic use.

At the same time, digital behavior is not inherently maladaptive. In many contexts, digital platforms facilitate learning, social connection, and health-related behavior change. For example, wearable technologies and mobile applications have been shown to support behavior modification through feedback loops, goal-setting mechanisms, and social accountability features (Del-Valle-Soto et al., 2024). Similarly, digital interventions leveraging artificial intelligence have demonstrated potential in promoting mental health and well-being by providing personalized support and adaptive feedback (Hao et al., 2025). These dual roles of digital technologies—as both facilitators of positive outcomes and potential sources of harm—underscore the need for nuanced analytical approaches that can differentiate between adaptive and maladaptive usage patterns.

Machine learning has emerged as a powerful methodological approach for analyzing complex behavioral data and identifying latent patterns that may not be apparent through traditional statistical techniques. Unlike conventional methods that rely on predefined hypotheses and linear relationships, machine learning algorithms can model nonlinear interactions and high-dimensional data structures, making them particularly suitable for studying multifaceted phenomena such as digital behavior (Khoei & Kaabouch, 2023). Clustering techniques, for instance, enable the identification of distinct user profiles based on patterns of behavior and psychological attributes, while classification models can predict group membership with high accuracy. Recent applications of machine learning in behavioral science have demonstrated its effectiveness in areas such as addiction classification, mental health prediction, and user segmentation (Huang et al., 2025; Vanna, 2025).

In addition to its analytical capabilities, machine learning also aligns with broader trends in personalized and adaptive systems. The ability to classify users into meaningful behavioral profiles has significant implications for the design of targeted interventions and personalized digital experiences. For example, health-related applications increasingly rely on user profiling to tailor content and recommendations based on individual preferences and behavioral tendencies (Gosetto et al., 2025). Similarly, reinforcement learning frameworks have been proposed to dynamically adapt digital environments in response to user behavior, thereby optimizing engagement and outcomes (Tang, 2025). These developments highlight the intersection of behavioral science and computational intelligence in advancing our understanding of digital ecosystems.

Furthermore, the integration of social learning theory into digital contexts provides a valuable theoretical foundation for interpreting behavior in online environments. Social learning theory posits that individuals acquire behaviors through observation, imitation, and reinforcement, processes that are amplified in digital spaces where social interactions are highly visible and rapidly disseminated (Liu et al., 2025). Digital platforms thus function as environments of continuous social feedback, where users not only consume content but also observe and emulate the behaviors of others. This dynamic interplay between individual predispositions and social influences reinforces the importance of considering both psychological and contextual factors in modeling digital behavior.

Despite these advances, significant gaps remain in the literature. Many studies continue to rely on unidimensional measures such as screen time, which fail to capture the complexity of digital engagement (Xu et al., 2025). Others focus on isolated variables without considering the interaction between usage patterns, reward sensitivity, and social reinforcement. Moreover, there is a lack of integrative models that combine psychological constructs with computational techniques to generate actionable insights. Addressing these gaps requires a holistic approach that leverages interdisciplinary perspectives and advanced analytical methods.

The present study seeks to contribute to this emerging field by employing a machine learning framework to identify distinct digital behavior profiles based on usage patterns, reward sensitivity, and social reinforcement. By integrating psychological theory with computational modeling, this research aims to provide a more comprehensive understanding of how individuals engage with digital environments and how these engagement patterns can be systematically categorized.

The aim of this study is to identify and classify digital behavior profiles using machine learning techniques based on individuals' usage patterns, reward sensitivity, and social reinforcement characteristics.

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2 Methods and Materials

2.1 Study Design and Participants

This study employed a cross-sectional, correlational design with an embedded machine learning modeling approach to identify latent digital behavior profiles based on psychological and behavioral predictors. The target population consisted of adult digital platform users residing in Canada. A total of 412 participants were recruited using a stratified online sampling strategy to ensure representation across age, gender, and socioeconomic strata. Inclusion criteria required participants to be between 18 and 60 years of age, have regular daily access to at least one digital platform (e.g., social media, streaming services, or online gaming), and provide informed consent for participation. Participants were recruited through online research panels and university-affiliated mailing lists. Data collection was conducted anonymously through a secure online survey platform.

2.2 Measures

Digital usage patterns were assessed using a structured self-report instrument developed to capture frequency, duration, and diversity of digital engagement across platforms. This instrument included items measuring daily screen time, multitasking behavior, platform switching frequency, and engagement intensity, operationalized through Likert-type scales. Reward sensitivity was measured using the Behavioral Activation System (BAS) scale originally developed by Carver and White (1994), which assesses individual differences in responsiveness to reward cues. The BAS scale includes subcomponents such as Drive, Fun Seeking, and Reward Responsiveness, and consists of 13 items rated on a four-point Likert scale. Social reinforcement was evaluated using a modified version of the Social Reinforcement Questionnaire, which captures perceived validation, feedback sensitivity, and reinforcement-seeking behavior in digital environments. This scale included 18 items rated on a five-point Likert scale and was adapted to reflect online social interactions such as likes, comments, and shares. All instruments used in the study have demonstrated acceptable psychometric properties in previous research, including strong internal consistency (Cronbach's alpha coefficients above 0.80) and construct validity across diverse populations. A pilot test with 30 participants was conducted prior to the main study to ensure clarity and reliability of the adapted measures.

2.3 Data Analysis

Data analysis was conducted using a combination of statistical and machine learning techniques. Initial preprocessing included data cleaning, handling of missing values using multiple imputation, and normalization of continuous variables. Descriptive statistics were computed to summarize participant characteristics and variable distributions. Pearson correlation analysis was performed to examine preliminary associations among usage patterns, reward sensitivity, and social reinforcement variables. For the primary analysis, unsupervised machine learning techniques were employed to identify distinct digital behavior profiles. Specifically, K-means clustering and hierarchical clustering methods were applied to standardized feature sets, with optimal cluster number determined using the silhouette coefficient and the Davies–Bouldin index. Feature importance and cluster interpretability were further examined using principal component analysis (PCA) to reduce dimensionality and visualize cluster separation. To enhance robustness, cluster stability was validated באמצעות bootstrapping procedures. Additionally, supervised learning models including random forest and support vector machines (SVM) were used in a secondary phase to predict cluster membership based on input variables, allowing evaluation of classification accuracy, precision, recall, and F1-score. All analyses were conducted using Python (scikit-learn library) and IBM SPSS Statistics (version 27), ensuring both statistical rigor and computational reproducibility.

3 Findings and Results

The final sample consisted of 412 participants residing in Canada. The mean age of participants was 31.84 years (SD = 9.27), with an age range spanning from 18 to 60 years. In terms of gender distribution, 53.2% identified as female, 45.1% as male, and 1.7% as non-binary or preferred not to disclose. Regarding educational attainment, 28.6% held a high school diploma, 46.8% had completed undergraduate studies, and 24.6% possessed postgraduate qualifications. Employment status indicated that 62.4% were employed full-time, 18.9% part-time, 10.7% students, and 8.0% unemployed or in other categories. On average, participants reported 5.73 hours (SD = 2.11) of daily digital platform usage, with social media being the most frequently used category (82.5%), followed by streaming services (68.4%) and online gaming (41.2%). These demographic and baseline usage characteristics suggest a diverse and digitally active sample suitable for behavioral profiling analysis.

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Table 1

Descriptive Statistics of Study Variables (N = 412)

Variable	Mean	SD	Minimum	Maximum
Daily Screen Time (hours)	5.73	2.11	1.20	11.80
Platform Switching Frequency	7.46	2.98	2.00	15.00
Multitasking Behavior	3.84	0.76	1.90	4.98
Engagement Intensity	4.12	0.69	2.10	5.00
BAS Drive	3.67	0.58	2.10	4.90
BAS Fun Seeking	3.92	0.63	2.00	5.00
BAS Reward Responsiveness	3.75	0.55	2.30	4.90
Social Reinforcement Sensitivity	4.01	0.72	2.20	5.00
Feedback Responsiveness	3.88	0.66	2.00	5.00
Reinforcement-Seeking Behavior	4.15	0.61	2.50	5.00

Table 1 presents the descriptive statistics for the primary study variables. The results indicate moderate to high levels across most behavioral and psychological constructs. Daily screen time averaged 5.73 hours, reflecting substantial engagement with digital environments. Platform switching frequency exhibited relatively high variability (SD = 2.98), suggesting heterogeneity in multitasking tendencies. Psychological measures revealed that participants scored highest on reinforcement-seeking behavior (M = 4.15, SD = 0.61) and engagement intensity (M = 4.12, SD = 0.69), indicating strong motivational and behavioral involvement in digital contexts. Reward sensitivity components (BAS subscales) demonstrated consistently elevated means, particularly in fun seeking (M = 3.92), highlighting the role of hedonic motivation in digital behavior. Overall, the distribution of variables supports the suitability of the dataset for clustering and profile identification.

Table 2

Cluster Centroids for Identified Digital Behavior Profiles

Variable	Cluster 1 (Low Engagement)	Cluster 2 (Balanced Users)	Cluster 3 (High Reinforcement Seekers)
Daily Screen Time	3.12	5.48	8.91
Platform Switching Frequency	4.21	7.05	11.83
Multitasking Behavior	2.98	3.76	4.62
Engagement Intensity	3.11	4.05	4.88
BAS Drive	3.02	3.65	4.21
BAS Fun Seeking	3.15	3.87	4.56
BAS Reward Responsiveness	3.09	3.72	4.33
Social Reinforcement Sensitivity	3.28	3.95	4.67
Feedback Responsiveness	3.14	3.81	4.52
Reinforcement-Seeking Behavior	3.36	4.02	4.78

The clustering analysis identified three distinct digital behavior profiles. Cluster 1, labeled "Low Engagement," consisted of individuals with comparatively low screen time, minimal multitasking, and reduced sensitivity to reward and social reinforcement cues. Cluster 2, labeled "Balanced Users," demonstrated moderate levels across all variables, indicating controlled and adaptive digital engagement patterns. Cluster 3, labeled "High Reinforcement Seekers," exhibited the highest values across all dimensions, particularly in screen time (M = 8.91) and reinforcement-seeking behavior (M = 4.78), suggesting a strong dependence on external validation and reward-driven interaction. The clear separation of centroids across clusters indicates robust differentiation among behavioral profiles.

Table 3

Classification Performance Metrics for Predicting Cluster Membership

Model	Accuracy	Precision	Recall	F1-Score

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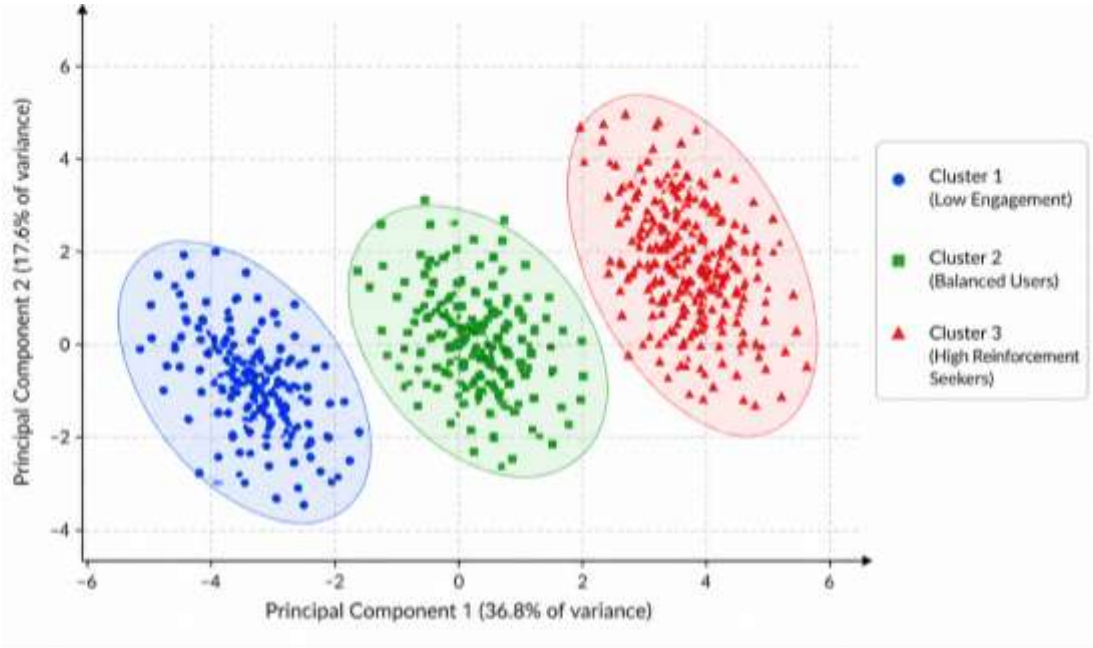
Random Forest	0.91	0.89	0.90	0.89
Support Vector Machine	0.87	0.85	0.86	0.85

The supervised classification models demonstrated high predictive performance in identifying cluster membership based on input variables. The random forest model achieved the highest overall accuracy (0.91), with balanced precision (0.89), recall (0.90), and F1-score (0.89), indicating strong generalization capability and robustness in classification. The support vector machine model also performed well, with slightly lower but still acceptable metrics. These results confirm that the identified behavioral profiles are not only distinct but also predictable using machine learning techniques, supporting the validity of the clustering solution.

Figure 1

Visualization of Digital Behavior Profiles Based on Principal Component Analysis (PCA)



The PCA-based visualization illustrated clear spatial separation among the three identified clusters, with minimal overlap between groups. The first two principal components accounted for a substantial proportion of variance, enabling effective dimensionality reduction while preserving cluster structure. Cluster 3 (High Reinforcement Seekers) was distinctly separated along the first principal component, reflecting its strong association with reward sensitivity and reinforcement variables. Cluster 1 (Low Engagement) occupied the opposite end of the spectrum, while Cluster 2 (Balanced Users) was positioned centrally, indicating intermediate characteristics. This visual confirmation reinforces the structural validity and interpretability of the clustering results.

4 Discussion

The present study aimed to identify distinct digital behavior profiles using machine learning techniques based on usage patterns, reward sensitivity, and social reinforcement. The findings revealed three clearly differentiated clusters: Low Engagement users, Balanced Users, and High Reinforcement Seekers. These profiles were characterized by systematic variations across behavioral intensity, motivational drivers, and responsiveness to social feedback. The clustering solution was robust, as evidenced by strong separation in the PCA visualization and high predictive accuracy of supervised models, particularly the random forest classifier. Collectively, these results support the assumption that digital behavior is not homogeneous but instead reflects structured patterns shaped by psychological and contextual factors.

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The identification of a Low Engagement cluster characterized by reduced screen time, limited multitasking, and lower reward sensitivity aligns with prior research suggesting that not all users are equally susceptible to the reinforcing properties of digital environments. Individuals in this group appear to exhibit greater behavioral regulation and lower dependence on external validation mechanisms. This pattern is consistent with findings indicating that lower reward sensitivity is associated with diminished responsiveness to digital reinforcement cues and reduced likelihood of compulsive engagement (Wegmann et al., 2025). Furthermore, the relatively low social reinforcement sensitivity observed in this cluster suggests a weaker reliance on peer feedback, which has been identified as a key driver of online engagement in previous studies (Véronneau & Schwartz-Mette, 2021). These results reinforce the notion that digital behavior must be understood in relation to individual differences in motivational systems.

In contrast, the Balanced Users cluster demonstrated moderate levels across all variables, reflecting a more adaptive pattern of digital engagement. This group appears to maintain a functional equilibrium between digital interaction and self-regulation, engaging with digital platforms without exhibiting excessive dependence. Such a pattern is consistent with research highlighting the potential for digital technologies to support positive outcomes when used in a controlled and intentional manner (Del-Valle-Soto et al., 2024). The moderate reward sensitivity and social reinforcement observed in this cluster suggest that these users benefit from digital engagement without becoming overly reliant on it. This finding is particularly important, as it challenges the binary distinction between problematic and non-problematic use, instead supporting a continuum-based perspective of digital behavior.

The High Reinforcement Seekers cluster represents the most critical profile identified in this study. Individuals in this group exhibited significantly elevated levels of screen time, engagement intensity, reward sensitivity, and social reinforcement. This pattern is indicative of a strong dependence on digital rewards and external validation, consistent with theoretical models of behavioral addiction. The findings align with evidence suggesting that digital platforms can exploit reward-processing mechanisms, leading to heightened engagement and potential overuse (Lakhan, 2025; Wang & Shen, 2025). Moreover, the high levels of reinforcement-seeking behavior observed in this cluster support the argument that intermittent and socially mediated rewards play a central role in sustaining digital engagement (Robayo-Pinzon et al., 2023). The pronounced separation of this cluster in the PCA space further underscores the distinctiveness of this behavioral pattern.

The strong predictive performance of machine learning models in classifying users into these clusters provides additional support for the validity of the identified profiles. The high accuracy achieved by the random forest model suggests that the combination of usage patterns, reward sensitivity, and social reinforcement constitutes a reliable feature set for behavioral classification. This finding is consistent with recent research demonstrating the effectiveness of machine learning in identifying patterns of digital addiction and behavioral segmentation (Huang et al., 2025; Vanna, 2025). Importantly, the use of both unsupervised and supervised techniques enhances the robustness of the analytical approach, allowing for both discovery and validation of behavioral profiles.

From a theoretical perspective, the results of this study can be interpreted through the lens of reinforcement learning and social learning frameworks. The elevated engagement observed in the High Reinforcement Seekers cluster reflects the operation of reinforcement loops, where behavior is continuously shaped by rewards and feedback. This is consistent with models suggesting that digital environments function as reinforcement systems that amplify reward-seeking tendencies (Tang, 2025). At the same time, the role of social reinforcement highlights the relevance of social learning theory, which posits that behavior is influenced by observation and interaction within a social context (Liu et al., 2025). The integration of these perspectives provides a comprehensive framework for understanding digital behavior as a product of both individual predispositions and environmental contingencies.

The findings also resonate with broader concerns regarding problematic digital use and its implications for mental health. The characteristics of the High Reinforcement Seekers cluster mirror those associated with digital addiction, including excessive use, loss of control, and reliance on digital interactions for emotional regulation (Amirthalingam & Khera, 2024; Shannon et al., 2025). The association between high reward sensitivity and increased engagement further supports the notion that certain individuals are more vulnerable to the addictive potential of digital technologies (Osser et al., 2025). Additionally, the observed patterns are consistent with research indicating that digital overuse may lead to diminished well-being and impaired functioning, particularly when driven by external validation and social comparison processes (Xu et al., 2025).

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At the same time, the study highlights the role of platform design in shaping user behavior. The high engagement levels observed in certain clusters may be partly attributable to persuasive design features that encourage continuous interaction. Prior research has documented how elements such as infinite scrolling and algorithmic personalization can reinforce habitual use and reduce self-regulation (Cemiloglu et al., 2021; Flayelle et al., 2023). The interaction between these design features and individual differences in reward sensitivity suggests a complex interplay between user characteristics and technological affordances. This interplay underscores the importance of considering both psychological and structural factors in the analysis of digital behavior.

The implications of these findings extend to the development of personalized interventions and digital well-being strategies. The identification of distinct behavioral profiles enables the design of targeted approaches that address the specific needs and vulnerabilities of different user groups. For example, individuals in the High Reinforcement Seekers cluster may benefit from interventions aimed at reducing reliance on external validation and enhancing self-regulation skills. Recent advances in AI-driven interventions suggest that personalized feedback and adaptive systems can effectively support behavior change in digital contexts (Hao et al., 2025). Similarly, the use of user profiling in mobile applications has been shown to improve engagement and outcomes by tailoring content to individual preferences (Gosetto et al., 2025). These approaches highlight the potential for leveraging machine learning insights to promote healthier digital behaviors.

Moreover, the findings contribute to ongoing discussions regarding the ethical design of digital technologies. The identification of user groups that are particularly susceptible to reinforcement mechanisms raises important questions about the responsibility of technology developers. The use of incentivization systems, including those based on tokenomics and reward structures, must be carefully balanced to avoid unintended consequences such as overuse or dependency (Jürjens et al., 2022; Roussille et al., 2023). As digital ecosystems become increasingly complex, there is a growing need for regulatory frameworks that address the behavioral impact of technology design.

In addition, the integration of machine learning into behavioral research reflects broader trends in computational social science and digital health. The ability to model complex interactions and identify latent patterns offers significant advantages over traditional analytical methods. However, it also introduces challenges related to interpretability, data privacy, and ethical use of algorithms (Khoei & Kaabouch, 2023; Shafay et al., 2022). The present study addresses some of these challenges by combining transparent clustering techniques with interpretable feature sets, but further work is needed to ensure responsible application of these methods.

The findings also align with research on digital ecosystems and the role of intelligent systems in shaping user behavior. Advances in computing infrastructure and adaptive systems enable increasingly sophisticated forms of personalization and behavioral prediction (Kokkonen et al., 2022; Trajano & Souza, 2024). These developments suggest that digital behavior will continue to evolve in response to both technological innovation and user adaptation. Understanding these dynamics requires ongoing research that integrates insights from psychology, computer science, and social theory.

5 Conclusion

Finally, the results underscore the importance of moving beyond simplistic measures of digital use toward more comprehensive models that capture the multidimensional nature of behavior. By incorporating usage patterns, reward sensitivity, and social reinforcement into a unified framework, this study provides a more nuanced understanding of digital engagement. This approach is consistent with recent calls for more integrative models that account for both individual differences and contextual factors in the study of digital behavior (Nasrollahi et al., 2023; Xu et al., 2025).

Despite its contributions, the present study is subject to several limitations that should be acknowledged. First, the cross-sectional design limits the ability to draw causal inferences regarding the relationships among usage patterns, reward sensitivity, and social reinforcement. Longitudinal designs would be necessary to examine how digital behavior profiles evolve over time and whether individuals transition between clusters. Second, the reliance on self-report measures introduces the possibility of response bias, particularly in the assessment of digital usage and psychological constructs. Although validated instruments were used, future studies could benefit from incorporating objective behavioral data such as digital logs or sensor-based measures. Third, the sample, while diverse, was limited to participants from a single national context, which may affect

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the generalizability of the findings to other cultural settings. Finally, while machine learning techniques offer powerful analytical capabilities, they also involve assumptions and parameter choices that may influence results. Further validation using alternative algorithms and datasets is recommended.

Future research should extend the present findings by adopting longitudinal and experimental designs to better understand the causal mechanisms underlying digital behavior profiles. Investigating how individuals move between clusters over time could provide valuable insights into the development and maintenance of problematic digital use. Additionally, future studies should explore the role of contextual factors such as cultural norms, platform-specific features, and environmental influences in shaping digital behavior. The integration of multimodal data sources, including behavioral tracking, physiological measures, and ecological momentary assessment, could enhance the precision and validity of behavioral profiling. Furthermore, there is a need to examine the effectiveness of personalized interventions tailored to specific user profiles, particularly in reducing excessive engagement among high-risk groups. Expanding research to diverse populations and cross-cultural contexts will also be essential for developing globally relevant models of digital behavior.

The findings of this study have important implications for practitioners, including mental health professionals, educators, and technology developers. Interventions aimed at promoting digital well-being should consider individual differences in reward sensitivity and social reinforcement, tailoring strategies to the specific needs of different user groups. For example, individuals exhibiting high reinforcement-seeking tendencies may benefit from cognitive-behavioral techniques that enhance self-regulation and reduce reliance on external validation. Technology developers should also incorporate ethical design principles that minimize the risk of excessive engagement, such as providing users with greater control over notifications and feedback mechanisms. In educational settings, digital literacy programs should emphasize not only technical skills but also critical awareness of the psychological processes underlying digital engagement. By leveraging insights from machine learning and behavioral science, practitioners can develop more effective and targeted approaches to fostering healthy and sustainable digital behaviors.

Authors' Contributions

All authors have contributed significantly to the research process and the development of the manuscript.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

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