Examining the Association Between Social Media Use and Self-Reported Social Energy Depletion: A Machine Learning Approach

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ABSTRACT

The pervasive integration of social media and digital technologies into daily life has been linked to a rise in digital fatigue and burnout. While the quantity of screen time is often implicated, the more nuanced behavioral patterns contributing to this phenomenon, termed "social energy depletion," are less understood. This study sought to move beyond simple correlational analyses by employing a machine learning framework to predict social energy depletion and identify its most significant behavioral predictors. This quantitative, cross-sectional study utilized a dataset of self-reported digital behavior and psychological metrics from 500 participants. A binary target variable for social energy depletion was created using a median split on a self-reported mood score. A key aspect of the methodology was feature engineering, creating interaction and polynomial features (e.g., screen_focus_ratio, sm_time_squared) to capture the context and non-linear effects of digital use. Three supervised machine learning models (Logistic Regression, Random Forest, Gradient Boosting) were trained and optimized using GridSearchCV to classify the presence of social energy depletion. The Gradient Boosting Classifier achieved the highest predictive accuracy at 58.7%. While the overall predictive power was modest, the feature importance analysis yielded the study's central finding. Engineered features representing the quality of attention (screen_focus_ratio) and the non-linear impact of social media duration (sm_time_squared) were among the most influential predictors, ranking third and fourth, respectively. This demonstrates that the context of digital engagement is a critical factor alongside the total volume of screen time. Predicting a complex psychological state like social energy depletion from behavioral data is challenging. However, this study successfully demonstrates that a machine learning approach can uncover complex, non-linear patterns that traditional analyses may miss. The findings strongly suggest that the quality and nature of digital engagement, not just the quantity, are key drivers of digital fatigue.

Keywords Digital Well-being, Feature Engineering, Machine Learning, Screen Time, Social Media

Introduction

The increasing prevalence and integration of digital technology into daily life have profound implications for mental well-being, particularly in the context of smartphone ubiquity and constant connectivity. The rise of such technologies has been linked to both positive and negative outcomes concerning mental health, necessitating a nuanced understanding of their impacts.

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The use of digital applications to support mental well-being has shown promise, particularly in healthcare settings. For instance, Hindman et al point out that digital technologies can enhance risk assessment, early detection, and personalized treatment, potentially leading to better outcomes for healthcare professionals, such as nurses, as they manage the stresses of their work environment [1]. Digital platforms can provide critical support systems, allowing individuals to seek help and resources more easily, thus addressing the growing concern of burnout and anxiety in these high-stress occupations. However, more recent evidence indicates that the perception of digital interventions varies significantly, and challenges remain in their adoption within mental health care [2]. Conversely, a study by Bellis et al highlights that excessive use of technology, particularly social media, poses risks to mental health, as high engagement was linked to addictive traits and perceived threats to mental well-being among adolescents [3] This duality underscores the complexity of digital use; while moderate engagement may be beneficial, excessive use can have detrimental effects, reinforcing the need for balanced technology consumption [4].

Social media platforms, integrated into the daily routines of many individuals, further complicate the relationship between digital connectivity and mental well-being. O'Reilly et al indicate that social media is a double-edged sword for adolescents, presenting both opportunities for social connection and risks of anxiety and low self-esteem, depending on individual engagement levels [5]. This perspective is echoed by Aschbrenner et al, who emphasize that access to online technologies is prevalent even among those with mental health challenges, showcasing the potential for digital interventions to promote mental health across various demographics [6]. However, it is essential to recognize the drawbacks associated with constant connectivity, which can lead to technostress—a form of stress resulting from the incessant demands of digital technologies in professional settings [7]. This stress can exacerbate feelings of burnout, as highlighted by Rotenstein et al, who stress that addressing burnout among healthcare providers is critical for enhancing their well-being [8].

As digital mental health interventions proliferate, ethical considerations surrounding their implementation become imperative. According to Wies et al, the design of digital health solutions must prioritize patient-centered approaches to effectively meet the needs of diverse populations, particularly younger individuals [9]. This approach seeks to mitigate the risks associated with digital technology while capitalizing on its potential to provide accessible mental health resources. Furthermore, transitioning to digital formats during the pandemic illustrated the critical importance of adaptability in mental health services to meet evolving sociocultural demands [10].

The phenomenon of "social energy depletion" can be conceptualized as the emotional and cognitive exhaustion stemming from digital interactions, particularly within the contexts of social media and continuous connectivity. This concept emphasizes the distinction between the quantity and quality of online engagement. While the quantity is often measured through metrics such as screen time and notification counts, quality is evaluated based on the context of usage, which differentiates between focused engagement and unfocused digital interactions.

The quantitative aspect of social energy depletion is defined by metrics such as screen time and notification counts. Prolonged screen exposure has been shown to correlate with increased emotional exhaustion. For instance, emotional exhaustion has been observed in various contexts where high screen time is common, leading to the depletion of psychological resources and negative health outcomes [11]. The cumulative effect of excessive notifications can create an overwhelming sense of urgency and distraction, which can exacerbate feelings of fatigue and emotional depletion across different social networks [12]. Studies indicate that higher levels of digital engagement are associated with diminished subjective well-being, suggesting that excessive digital interaction is detrimental to mental health [13].

Conversely, the quality of digital engagement significantly impacts social energy levels. Notably, focused engagement—characterized by deliberate and meaningful interaction—tends to foster a more positive emotional state compared to unfocused or passive consumption of digital content. Hall and Davis articulate that interactions differ in their energy expenditure based on context, where energy-intensive interactions, such as those involving deep emotional connection, are more depleting than less intensive interactions [12]. Moreover, research on teachers has shown that those exhibiting higher emotional exhaustion report poorer quality interactions, highlighting that emotionally exhausted individuals often engage in less meaningful exchanges, which impacts both personal satisfaction and professional effectiveness [14]. The concept of "emotional inertia," presented by Alessandri et al, underscores how continuous emotional exhaustion can lead to a cycle of reduced emotional regulation abilities, thereby compromising the quality of future engagements [15].

Recognizing both quantity and quality is crucial for managing digital interactions effectively to mitigate social energy depletion. Strategies aimed at balanced engagement, which emphasize the need for mindful and focused digital interactions, have been suggested to counter the adverse effects of constant connectivity [16]. By prioritizing quality content and connections over sheer volume, it is possible to enhance psychological resilience and reduce the risk of emotional exhaustion.

This study aims to address a significant gap in the existing literature on digital well-being. While previous research has successfully established a link between social media use and negative psychological outcomes, these studies have often relied on simple linear correlations, which may not fully capture the intricate nature of digital behavior. The primary goal of this research is, therefore, to move beyond correlational analysis and develop a predictive model for social energy depletion using digital behavior metrics. The novelty of our approach lies in the application of a comparative machine learning framework, which is specifically designed to identify the complex, non-linear patterns and interaction effects that are likely characteristic of how individuals engage with technology.

Our central hypothesis is that the context of digital use is a more powerful predictor of social energy depletion than the raw quantity of use alone. We propose that engineered features, such as the ratio of screen time to focus, will prove to be more significant predictors than simple metrics like total screen time. To investigate this, the paper is structured as follows: First, we will review the relevant literature on the psychology of social media and digital burnout. Next, the methodology section will detail our feature engineering process and the machine learning pipeline. Subsequently, we will present the results of our predictive models and a feature importance analysis. Finally, the paper will conclude with a discussion of the findings, their implications, and directions for future research.

Literature Review

Psychology of Social Media

The psychology of social media encompasses a myriad of cognitive and emotional effects that significantly influence user behavior. Two notable concepts within this domain are social comparison theory and the impact of notifications through variable rewards, which contribute to compulsive usage patterns.

Social comparison theory, as articulated by Festinger, posits that individuals have an innate drive to evaluate themselves relative to others, which is particularly pronounced on image-centric social media platforms such as Instagram and Snapchat. These platforms serve as a breeding ground for social comparison due to their emphasis on visual content, often portraying idealized versions of life that can lead to feelings of inadequacy among users. Research [5] discuss the consequential impact of social media on adolescent mental health, highlighting that users often perceive their own lives as less fulfilling when compared to the curated images and experiences posted by peers, resulting in diminished self-esteem and increased anxiety [5]. Additionally, [3] underscore the perception of social media as a threat to mental well-being, validating that high levels of digital use, particularly for entertainment, can promote mood and anxiety disorders, especially among adolescents [3].

On the other hand, the role of intermittent variable rewards from notifications is instrumental in shaping compulsive usage patterns reminiscent of behavioral addiction. When users receive notifications, they experience a burst of dopamine—a neurotransmitter associated with pleasure and reward—which reinforces the desire to engage with their devices. The intermittent nature of these rewards creates a compelling cycle that can lead to compulsive behaviors. Research [17] examined the psychological mechanics behind digital engagement, noting that notifications often trigger a reinforcement loop compelling users to check their devices frequently, despite potential detrimental effects on their mental health [17]. This aligns with the findings of [4], who propose that excessive engagement with digital platforms can lead to maladaptive behaviors characterized by a greater preference for immediate gratification over long-term rewards [4]. Such engagement fosters a cycle where the immediate rewards obtained from notifications outweigh the negative repercussions tied to compulsive usage, thus perpetuating a cycle of addiction.

The relationship between behavioral cues and reward systems can be seen in the framework provided by [18], which elucidates how the variability of rewards—such as likes and notifications—can escalate the compulsive seeking of digital engagement [18]. The connection between psychological and neural pathways associated with reward processing is supported by studies indicating that regions of the brain responsible for anticipation and reward are engaged during digital interactions, confirming the neurobiological underpinnings of compulsion in the face of variable rewards [19].

Digital Well-being and Burnout

The growing phenomenon of digital fatigue and its connection to burnout has garnered significant attention in recent research, particularly given the increasing reliance on digital technology in both personal and professional arenas. Digital fatigue refers not only to mental exhaustion resulting from excessive screen time and digital interactions but also to its physiological implications, such as disruptions in sleep and increased anxiety. Understanding frameworks for digital wellness, including the concept of "digital hygiene," is essential to mitigating these challenges.

Research highlights a potential connection between excessive digital engagement and mood disorders, particularly anxiety and depression. Digital saturation, characterized by high screen time and incessant engagement with digital platforms, is linked to decreased mental well-being. For instance, [20] found that emerging adults who spend significant time on social media exhibit poor mental health outcomes associated with addictive usage patterns, thereby highlighting a direct link between prolonged digital engagement and negative psychological states [20] Similarly, [21] noted that sustained digital interactions could lead to increased mental fatigue, which manifests in impaired cognitive processing and decision-making [21]. The identified pattern of dependency on technology and the emotional weight it carries contributes substantially to feeling overwhelmed, emphasizing the urgent need for digital well-being strategies.

In response to the challenges of digital fatigue, frameworks for promoting digital wellness—often encapsulated in the concept of "digital hygiene"—have emerged. Digital hygiene encompasses practices that help individuals maintain a healthy relationship with technology, such as managing screen time, prioritizing meaningful interactions, and avoiding detrimental content consumption. Research [22] argue that creating a culture prioritizing digital well-being can improve job satisfaction and mental health among employees, highlighting the significance of institutional support in establishing these practices [22] They emphasize that employers should cultivate environments where employees feel supported in adopting healthier digital habits, thereby fostering personal well-being conducive to productivity.

The physiological symptoms of burnout—such as sleep disruption—are also closely tied to excessive screen time and constant connectivity. Extensive screen exposure has been shown to negatively influence sleep quality, with consequences manifesting as fatigue and cognitive impairments. Research [23] conducted a systematic review that identified a strong correlation between insufficient sleep and increased odds of depression among physicians, linking professional fatigue not only to work-related stress but also to inadequate recovery periods between such engagements [23]. Furthermore, [24] highlighted that high mental workloads, often exacerbated by continuous digital engagement, directly correlate with increased levels of mental fatigue and poor sleep quality, illustrating the cumulative effect of digital exposure on overall well-being [24].

Quantitative Approaches

Numerous quantitative approaches have been employed in investigating digital behavior data, particularly as they relate to mental health outcomes, digital fatigue, and burnout. However, notable gaps exist in the current research landscape that merit further exploration.

First, common metrics utilized in prior studies typically include self-reported screen time and app usage logs. Self-reported measures are prevalent due to their ease of data collection; they enable researchers to gather subjective insights into users' perceptions of their digital engagement and its corresponding effects on well-being [25]. Bennett et al discuss the utility of these self-reported metrics in analyzing psychological experiences such as emotional exhaustion in diverse contexts, emphasizing their effectiveness for understanding participant experiences [25]. Similarly, studies using app usage logs provide objective data regarding the frequency and nature of digital interactions, although they often lack the nuanced insights necessary for a comprehensive understanding of user behavior and the psychological implications of their usage patterns.

Despite the availability of these metrics, gaps persist in their incorporation into more sophisticated analytical frameworks. Specifically, previous analyses have largely overlooked advanced feature engineering to capture interaction effects within the data. Liu and Zhou highlight the importance of integrating interaction terms among multiple variables to uncover deeper insights into emotional exhaustion [26]. The simplistic modeling of digital behavior data has often resulted in the neglect of complex variables contributing to burnout and fatigue.

Furthermore, many studies focusing on digital interventions, such as those evaluating the effectiveness of health apps, have typically analyzed group-level data without considering individual variability in user behavior and context, as indicated by [27]. This oversight limits the potential to draw actionable insights that could lead to the optimization of digital health solutions and personalized user experiences.

Method

Research Design

This study employed a quantitative, cross-sectional research design to investigate the association between digital behaviors and self-reported social energy depletion. This design is particularly well-suited for capturing a snapshot of the prevalence and patterns of digital habits and their concurrent psychological states within a specific population at a single point in time. A supervised machine learning approach was utilized to move beyond simple correlational analysis and build predictive classification models. This approach was chosen for its ability to identify complex, non-linear relationships and interaction effects between variables that traditional linear models might fail to capture. The primary goal was to classify individuals into one of two categories—experiencing social energy depletion or not—based on a combination of raw and engineered digital behavior metrics, thereby testing the feasibility of using behavioral data to predict a state of digital fatigue.

Data Source and Participants

The analysis was conducted on the dataset.csv file, a collection of self-reported data from 500 participants (N=500). The dataset is composed of a convenience sample, and it contains a rich variety of metrics designed to capture different facets of an individual's daily life and digital footprint. These metrics can be broadly categorized into behavioral logs (daily screen time, social media usage, notification counts), physiological data (sleep duration), and psychometric scales (scores from assessments measuring mood, focus, and anxiety levels). The inclusion of these diverse data types allows for a more holistic examination of the factors potentially contributing to digital well-being.

Measures and Operationalization

The dependent variable, social_energy_depletion, was operationalized to create a binary outcome suitable for the supervised classification task. This was achieved by first calculating the median of the continuous mood_score variable, which was determined to be 9.0 on its scale. A new binary feature was then engineered where a value of '1' was assigned to participants with a mood score at or below the median, representing the presence of social energy depletion. Conversely, a value of '0' was assigned to those with a score above the median. This median split was chosen as a pragmatic approach to create balanced classes, a condition that is highly beneficial for training and evaluating supervised classification models by preventing the algorithm from becoming biased towards a majority class. While this transformation simplifies a complex psychological continuum, it creates a tractable and meaningful target for a predictive modeling framework. The independent variables initially included raw metrics such as daily_screen_time_min, social_media_time_min, notification_count, sleep_hours, and anxiety_level, each serving as a direct measure of behavior or psychological state.

Feature Engineering

To capture more nuanced and contextual aspects of digital engagement, a comprehensive feature engineering process was undertaken. This process is critical for translating raw data into informative signals for the machine learning models and is guided by the central hypothesis that the context and patterns of digital behavior are more predictive of fatigue than raw usage metrics alone.

Two interaction features were created to test hypotheses about the quality of digital engagement. The first, screen_focus_ratio (calculated as daily_screen_time_min / focus_score), was designed to proxy for the quality of attention during screen use. A high value suggests that extensive screen time is paired with low focus, potentially indicating highly fragmented or distracting digital sessions that could impose a greater cognitive load. The second, notifications_per_screen_minute (calculated as notification_count / daily_screen_time_min), was intended to measure the density of interruptions. This feature is grounded in psychological theories of intermittent reinforcement, where a high density of notifications may foster a state of hyper-vigilance and continuous partial attention, thereby draining cognitive resources.

Furthermore, to model potentially non-linear, dose-response relationships, two polynomial features were generated by squaring key predictors: sm_time_squared and sleep_squared. The sm_time_squared feature was created to test the hypothesis that the negative impact of social media might accelerate after a certain threshold, representing a "tipping point" beyond which its effects become disproportionately detrimental. Similarly, sleep_squared allows the model to capture the non-linear relationship between sleep and well-being, where the marginal benefit of an extra hour of sleep may diminish at higher levels.

Data Analysis Procedure

The data analysis pipeline was systematically constructed and consisted of data preprocessing, comparative model selection with rigorous hyperparameter tuning, and a final, multifaceted evaluation.

The dataset, including all original and engineered features, was first partitioned into a training set (70% of the data) and a testing set (30%). A stratified split based on the social_energy_depletion target variable was employed to ensure that the proportional representation of each class was maintained in both the training and testing sets. This step (random_state=42) is crucial for preventing sampling bias and ensuring that the model's evaluation is reliable. Subsequently, feature scaling was applied using the StandardScaler, which standardizes each feature by removing the mean and scaling to unit variance. This normalization is a critical prerequisite for the optimal performance of regularized models like Logistic Regression and other algorithms that are sensitive to the scale of input features.

A comparative modeling approach was adopted to evaluate the performance of different algorithmic assumptions. Three distinct supervised learning algorithms were selected: Logistic Regression, chosen as a powerful and highly interpretable linear baseline model; Random Forest Classifier, a bagging ensemble method known for its robustness and ability to capture complex interactions while mitigating overfitting; and Gradient Boosting Classifier, a boosting ensemble method that often achieves state-of-the-art performance by sequentially building models that correct the errors of their predecessors. To optimize the predictive performance of each model, a hyperparameter tuning process was conducted using GridSearchCV with 5-fold cross-validation (cv=5). This exhaustive search method systematically works through a predefined grid of parameters, ensuring that the selected hyperparameters are robust and generalize well to unseen data. For Logistic Regression, the regularization parameter C was tuned over [0.01, 0.1, 1, 10]. For Random Forest, n_estimators, max_depth, and min_samples_leaf were tuned. For Gradient Boosting, n_estimators, learning_rate, and max_depth were tuned.

The final performance of each tuned model was evaluated on the held-out test set. Accuracy was chosen as the primary evaluation metric due to its straightforward interpretation, a choice justified by the balanced class distribution achieved through the median split. In addition to the primary accuracy score, the full classification report, including precision and recall for each class, was also examined to provide a more nuanced understanding of model performance. To identify the key drivers of the prediction, feature importance scores were extracted from the best-performing model—using the .feature_importances_ attribute for tree-based models or the .coef_ attribute for Logistic Regression—for final interpretation.

Result and Discussion

This section presents the performance of the predictive models and provides an in-depth discussion of the feature importance findings, interpreting their implications for understanding social energy depletion.

Model Performance

The analysis involved training and tuning three distinct machine learning models to classify social energy depletion. After hyperparameter optimization using 5-fold cross-validation, the models were evaluated on the held-out test set. The Gradient Boosting Classifier emerged as the top-performing model with a final accuracy of 58.7%, followed closely by Logistic Regression at 58.0%, and the Random Forest Classifier at 56.7%. The classification report for the Gradient Boosting model revealed a precision of 0.58 and a recall of 0.70 for the positive class (depletion), indicating it was more effective at correctly identifying individuals who were experiencing social energy depletion than it was at correctly identifying those who were not, albeit with a significant number of false positives.

The modest accuracy scores, peaking just under 59%, are a significant finding in themselves. They suggest that predicting a complex, internal psychological state like social energy depletion from the available self-reported behavioral data is an inherently challenging task. This level of performance, while statistically better than a random guess, points toward a "performance ceiling" for this type of data. This ceiling is likely not a reflection of inadequate modeling techniques—as both linear and complex non-linear models performed similarly—but rather a testament to the inherent noise, variability, and unmeasured confounding variables in human behavior. Factors such as an individual's resilience, social support systems, offline stressors, and the specific nature of their online interactions are powerful moderators that were not captured in the dataset. The results indicate that while a clear predictive signal exists within digital behavior patterns, it is not strong enough on its own to achieve high-precision classification, highlighting the multifaceted and deeply personal nature of digital well-being.

Feature Importance: The Central Finding

The core insights of this study are derived from the feature importance analysis of the best-performing model, the Gradient Boosting Classifier, as shown in figure 1. The analysis revealed the relative influence of each variable in predicting social energy depletion, with the results underscoring the critical success of the feature engineering process. The top five most influential features were, in order: daily_screen_time_min, social_media_time_min, screen_focus_ratio, sm_time_squared, and notifications_per_screen_minute.

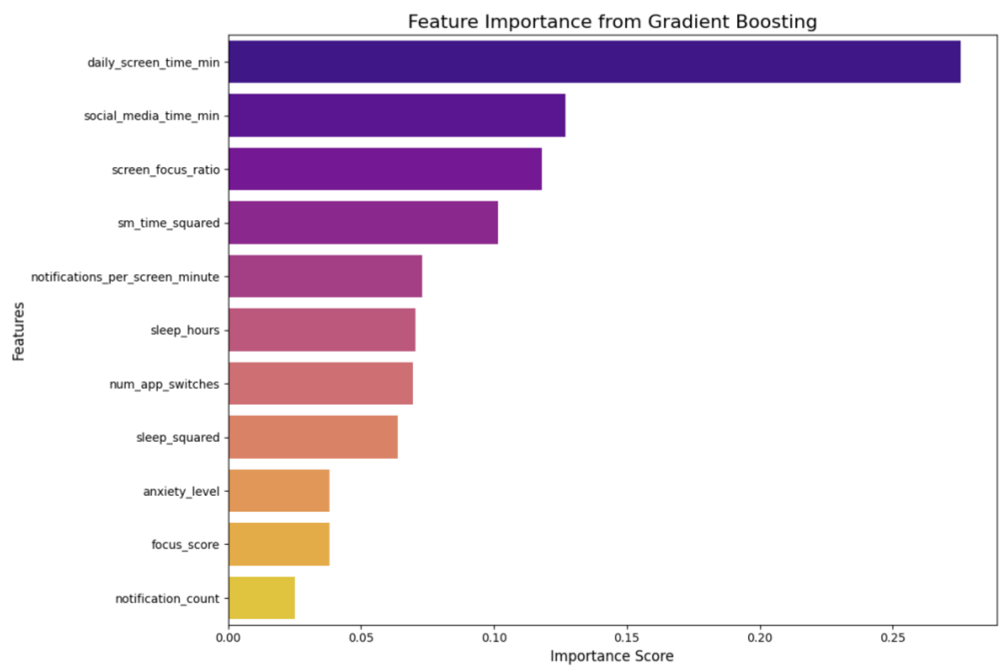

Figure 1 **Feature Importance from Gradient Boosting**

The most significant finding is the high ranking of the engineered features, screen_focus_ratio and sm_time_squared, which were the third and fourth most important predictors, respectively. While the raw quantity of screen time (daily_screen_time_min) was the single most important feature—confirming the foundational hypothesis that sheer volume of digital engagement is a key factor—the prominence of the engineered features reveals a more nuanced and actionable story. The importance of screen_focus_ratio strongly suggests that the context of screen use is nearly as critical as its duration. A high value for this feature, representing extensive screen time paired with low self-reported focus, is a powerful predictor of depletion. This finding provides empirical support for the idea that fragmented, distracted, and unfocused digital sessions—characterized by constant task-switching and a lack of deep engagement—impose a significant cognitive load that directly contributes to feelings of mental and emotional exhaustion.

Furthermore, the importance of the sm_time_squared feature provides compelling evidence for a non-linear, "tipping point" effect in social media consumption. Its influence suggests that the negative impact of social media use is not constant but accelerates as time spent on these platforms increases. This aligns with psychological theories of diminishing returns, indicating that while moderate use may have a manageable or even positive effect, excessive use can become disproportionately detrimental to an individual's social energy reserves. Collectively, these findings demonstrate that a holistic understanding of digital fatigue requires moving beyond simple metrics of quantity to also consider the quality of attention and the non-linear nature of engagement.

Comparison with Previous Research

These findings both align with and extend previous research in the field of digital well-being. Many prior studies, often relying on traditional statistical methods like linear regression, have established a simple linear correlation between screen time and negative psychological outcomes such as anxiety and depression. This study confirms the importance of raw usage metrics like daily_screen_time_min as a primary predictor, grounding our results in the existing literature. However, by employing a machine learning framework and deliberate feature engineering, this work advances the conversation significantly. The high importance of features like screen_focus_ratio and sm_time_squared provides quantitative evidence for more complex theories of digital fatigue that emphasize the quality and pattern of engagement, not just the quantity. This moves beyond the often-simplistic public health message of "less screen time" to a more nuanced understanding that how time is spent online is a critical factor—a concept discussed theoretically in the literature but less frequently demonstrated through predictive modeling. Our approach, therefore, serves as a methodological bridge, showing how computational techniques can validate and expand upon established psychological theories.

Limitations of the Study

Despite these contributions, several limitations must be acknowledged as they provide context for the results. First, the cross-sectional nature of the data is a primary constraint, preventing any inference of causality. While we can identify strong associations between certain digital behaviors and social energy depletion, we cannot determine the direction of this relationship. It is equally plausible that specific usage patterns cause depletion as it is that individuals who are already feeling depleted engage with technology differently, perhaps as a form of avoidance or distraction. Second, the reliance on self-reported data introduces the potential for systematic biases, including recall bias (inaccurately remembering usage) and social desirability bias (underreporting behaviors perceived as negative). Objective data, such as that collected directly from device APIs, would provide a more reliable foundation for analysis. Finally, the operationalization of the target variable—creating a binary social_energy_depletion feature from a continuous mood_score—is a necessary simplification for a classification task but one that sacrifices information. This approach loses the nuance of the original scale and treats a multifaceted construct as a simple binary outcome, potentially obscuring more subtle relationships.

Future Research Directions

The findings and limitations of this study point toward several promising avenues for future research. A longitudinal study design is the most critical next step. Tracking individuals' digital behaviors and well-being over an extended period would allow for the examination of temporal precedence, helping to untangle the causal relationships between digital habits and shifts in mental state. Furthermore, future work should aim to incorporate more objective and granular data. This could include passively sensed data on app usage, distinguishing between active engagement (e.g., posting, messaging) and passive consumption. Analyzing the sentiment of content being consumed or the emotional tone of online conversations could also provide invaluable context. Such rich, multi-modal data would likely improve predictive accuracy and yield deeper insights into the specific mechanisms that drive social energy depletion in our increasingly connected world.

Conclusion

In conclusion, this study demonstrated the potential and the inherent challenges of using machine learning to predict social energy depletion from self-reported digital behavior data. While the models achieved a modest predictive accuracy of approximately 59%, the investigation yielded a crucial insight: the context and pattern of digital engagement are as important, if not more so, than the sheer quantity of time spent online. The prominence of engineered features, specifically the screen_focus_ratio and the non-linear sm_time_squared, successfully moved the analysis beyond simple linear relationships. These findings suggest that unfocused, fragmented screen time and an accelerating, detrimental effect of excessive social media use are significant predictors of digital exhaustion. The research provides empirical support for a more nuanced public health message that prioritizes the quality of digital interactions over simplistic directives to merely reduce screen time.

Ultimately, this work underscores the complexity of the relationship between technology use and mental well-being. The study's limitations, particularly its reliance on cross-sectional and self-reported data, highlight the need for future research to employ longitudinal designs with objective, passively sensed data. By capturing more granular details about user behavior—such as the distinction between active and passive consumption or the sentiment of content engaged with—subsequent studies can build upon this foundation to develop more accurate predictive models. Such advancements hold the potential to inform the design of digital well-being tools that can offer personalized, context-aware interventions, helping users foster a healthier and more sustainable relationship with technology.

Declarations

Author Contributions

Conceptualization: V.K.P.; Methodology: P.S.; Software: M.B.; Validation: P.S.; Formal Analysis: V.K.P.; Investigation: P.S.; Resources: M.B.; Data Curation: M.B.; Writing Original Draft Preparation: V.K.P.; Writing Review and Editing: P.S.; Visualization: V.K.P.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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