

Digital Dependency and Attention Regulation among Emerging Adults

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Abstract — Digital platforms have become embedded in the academic, occupational, and social routines of emerging adults, raising questions about their relationship with sustained and self-regulated attention. This study conceptualizes digital dependency as a multidimensional behavioural pattern involving compulsive checking, notification reactivity, task-switching, and difficulty disengaging rather than simply prolonged screen exposure. A key research gap is the limited integration of behavioural digital-use indicators with objective measures of attentional regulation in emerging adults aged approximately 18–29 years. The proposed research addresses this gap through a multimodal framework combining self-reported digital dependency, smartphone-derived behavioural indicators, computerized attention tasks, and contextual variables. Particular emphasis is placed on distinguishing duration of digital exposure from fragmentation of attention, because equal screen-time levels may represent substantially different patterns of cognitive interruption. The study further proposes machine-learning modelling to identify behavioural configurations associated with weak attentional control while avoiding the assumption that digital use necessarily causes attention impairment.

Keywords — Digital Dependency; Attention Regulation; Emerging Adults; Problematic Smartphone Use; Digital Behaviour; Machine Learning

Introduction

Digital technology is no longer an occasional environmental stimulus for emerging adults; it forms part of the infrastructure through which education, employment, social relationships, entertainment, financial transactions, and

information seeking are organized. Smartphones are particularly important because they combine multiple streams of stimulation within a device that remains continuously accessible. Messaging, short-form video, social networking, gaming, academic applications, electronic commerce, and algorithmically personalized information can therefore compete for attention within the same behavioural environment.

This technological integration should not automatically be interpreted as harmful. Digital environments provide substantial opportunities for communication, learning, social support, and access to information. Recent institutional assessments similarly emphasize that the effects of digital engagement are heterogeneous rather than uniformly negative. The World Health Organization (WHO), for example, has characterized digital environments as simultaneously offering opportunities and risks for young people's mental health and well-being. Consequently, an analytically useful research question is not whether digital technology is intrinsically beneficial or harmful, but **which patterns of engagement are associated with reduced capacity to regulate attention and under what circumstances.**

This distinction becomes particularly relevant during emerging adulthood. The period commonly spanning the late teenage years through the twenties is characterized by increased autonomy, changing educational and occupational responsibilities, intensified social networking, and greater responsibility for managing one's own time. Unlike younger adolescents, emerging adults frequently operate without externally imposed restrictions on device access. Academic assignments, professional communication, leisure activities,

and social relationships may all occur through the same screen. This convergence can make the boundary between purposeful and compulsive digital behaviour difficult to identify.

The present manuscript uses the term **digital dependency** to describe a behavioural tendency characterized by persistent urges to engage with connected devices or platforms, difficulty disengaging, habitual checking, responsiveness to digital cues, and continued engagement despite interference with intended activities. This conceptualization intentionally differs from a simple screen-time measure. An individual may spend several hours using a laptop for uninterrupted academic work without experiencing substantial attentional fragmentation, whereas another person may accumulate a shorter duration of use through hundreds of brief checks, application transitions, notifications, and interruptions. Total exposure therefore cannot adequately represent the structure of digital behaviour.

The contemporary digital environment adds another dimension to this problem: **attention fragmentation**. Digital interfaces frequently present alerts, recommendations, badges, messages, rapidly changing audiovisual content, and opportunities for immediate task switching. The cognitive consequence may therefore depend less on how long a person remains digitally connected than on how frequently attention is redirected. Repeated transitions between academic work, messaging applications, social media feeds, and entertainment platforms may generate a pattern in which sustained goal-directed attention competes with habitual responses to digital cues.

Recent evidence reinforces the importance of separating problematic patterns from digital exposure itself. A 2026 systematic review examining social media use and adolescent inattention and impulsivity synthesized 25 studies and reported that problematic social-media use was commonly associated with inattention-related outcomes, while also stressing substantial methodological heterogeneity and the inability of predominantly cross-sectional evidence to establish directionality. Although the review concerned adolescents rather than the emerging-adult population targeted here, its findings illustrate a broader methodological problem: association between digital behaviour and attention does not establish whether problematic engagement weakens attentional regulation, pre-existing attentional difficulties encourage frequent digital engagement, or both processes operate simultaneously.

This bidirectionality is central to the present research framework. An individual with weaker inhibitory control may be especially responsive to notifications or immediate digital rewards. Frequent interruption may subsequently make sustained task engagement more difficult, potentially reinforcing the original behaviour. WHO's 2025 policy assessment likewise notes that relationships between technology use and mental-health outcomes can be bidirectional and shaped by individual and environmental factors. Although mental health and attention are distinct outcomes, this broader observation cautions against simplistic exposure–effect models.

1.1 Research Gap

The principal research gap identified in this manuscript is the **insufficient differentiation between digital exposure intensity and digital interruption structure when explaining attention regulation among emerging adults**.

Much existing work operationalizes digital behaviour through self-reported screen time, frequency of social-media use, or problematic-use questionnaires. These measures provide useful information but may obscure behaviourally meaningful differences. Two participants reporting four hours of smartphone use may differ substantially in notification

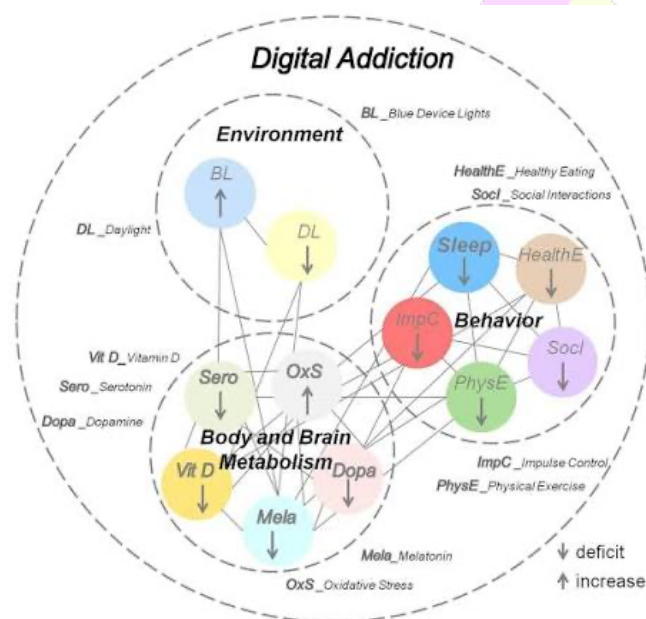


Fig. 1: Digital Addiction and Sleep

Source: <https://www.mdpi.com/1660-4601/19/11/6910>

Attention regulation is similarly broader than the ability to concentrate for a fixed period. It incorporates the capacity to maintain task-relevant attention, inhibit irrelevant responses, resist distraction, redirect attention after interruption, and allocate cognitive resources according to current goals. These processes overlap with executive functioning. A systematic review of mobile technology and executive functioning in healthy adults aged 18–35 found that the available literature was relatively limited and methodologically heterogeneous, highlighting the need for stronger evidence concerning specific aspects of technology use and executive functioning.

frequency, number of device pickups, duration of uninterrupted sessions, application-switching behaviour, night-time engagement, and proportion of goal-directed versus habitual use.

A second limitation concerns outcome measurement. Studies relying entirely on self-reported distractibility may partly measure participants' perceptions about their digital habits rather than their actual attentional performance. Conversely, laboratory attention tasks without ecologically relevant behavioural information may not capture the fragmented conditions under which digital distraction occurs in everyday life.

A third gap involves predictive integration. Relatively limited research has examined whether combinations of behavioural features can identify attention-regulation vulnerability more effectively than screen duration alone. This creates an opportunity for machine-learning methods—not as diagnostic substitutes, but as tools for detecting nonlinear interactions among multiple digital-behaviour variables.

The proposed study therefore introduces an **Attention Fragmentation–Dependency Framework (AFDF)** in which digital dependency is decomposed into behavioural dimensions such as compulsive checking, notification responsiveness, application switching, late-night engagement, and difficulty disengaging. These variables will subsequently be examined against objective and subjective indicators of attention regulation.

1.2 Research Objective

The primary objective is to determine whether **fragmented and dependency-oriented patterns of digital engagement explain variation in attention regulation among emerging adults more effectively than total screen duration alone.**

More specifically, the proposed investigation seeks to examine relationships between digital dependency and sustained attention, identify which behavioural features carry the strongest predictive information, evaluate the contribution of sleep and psychological context, and construct interpretable machine-learning models capable of estimating attention-regulation profiles from multimodal behavioural data.

The study does not begin with the presumption that smartphones or social media directly cause attentional impairment. Instead, it treats digital dependency and attention regulation as potentially reciprocal phenomena influenced by contextual and individual differences.

Literature Review

2.1 From Screen Time to Digital Dependency

Earlier approaches to technology-related behaviour frequently emphasized exposure duration. Screen time remains useful because it is understandable and comparatively easy to quantify, but the measure becomes increasingly crude when digital technology supports heterogeneous activities. Reading an academic article, participating in an online class, video calling a family member, repeatedly refreshing a social-media feed, and responding compulsively to notifications may produce equivalent minutes of exposure while involving different cognitive processes.

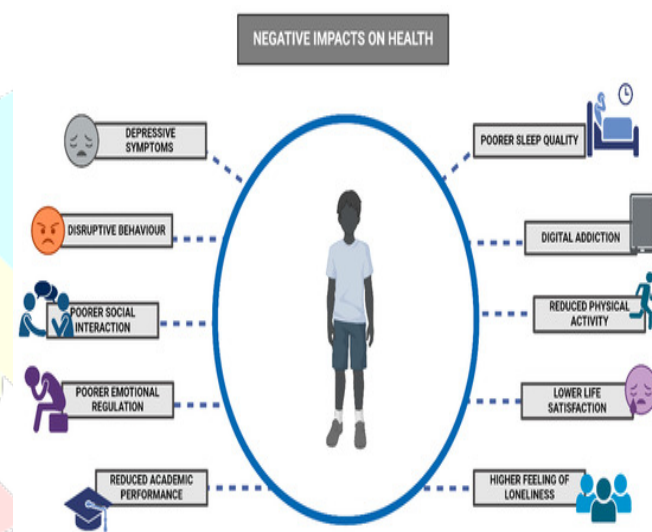


Fig. 2: Digital Device Usage and Childhood Cognitive Development

Source: <https://www.mdpi.com/2227-9067/11/11/1299>

The literature has therefore increasingly considered problematic smartphone or internet use. Problematic smartphone use generally incorporates excessive or difficult-to-control engagement accompanied by negative consequences. A longitudinal investigation of 385 undergraduates, for example, examined problematic smartphone use alongside psychological flexibility, anxiety, and sleep disturbance, illustrating the importance of studying behavioural dysregulation rather than exposure duration in isolation.

The distinction is important because dependency-oriented behaviour may be partly automatic. Device checking can occur without a clearly articulated informational goal. Environmental cues—including notification sounds, screen illumination, boredom, task difficulty, or anticipation of social feedback—may initiate interaction before deliberate decision-making occurs. Digital dependency can consequently be conceptualized as a problem of **behavioural control and attentional allocation**, not simply excessive consumption.

Large-scale international evidence provides additional context for the transition toward problematic-use constructs. WHO's 2021/2022 Health Behaviour in School-aged Children study covered adolescents across 44 countries and regions and reported substantial levels of continuous online contact alongside problematic social-media and gaming behaviour. These adolescent findings cannot be directly generalized to emerging adults, but they demonstrate that intensive connectivity increasingly precedes adulthood and may form part of the behavioural background with which young people enter university and employment.

2.2 Attention Regulation in Digitally Dense Environments

Attention regulation requires selection. Because multiple stimuli continuously compete for finite cognitive resources, goal-directed behaviour depends on suppressing information that is currently irrelevant. Digital environments can increase this competition by making alternative activities immediately available.

Notifications represent one obvious source of interruption, but attentional disruption need not require an external alert. Internally initiated checking can also interrupt a task. A student writing an assignment may voluntarily open a messaging application, subsequently visit a social platform, watch recommended content, and return to the assignment several minutes later. The resulting disruption is better characterized as a sequence of **attention transitions** than as a discrete period of screen exposure.

Such transitions matter because returning physically to a task does not necessarily imply immediate restoration of the previous attentional state. Repeated switching can therefore create a working environment dominated by short cognitive episodes rather than prolonged goal-directed engagement.

Research linking mobile technology to executive functioning nevertheless remains difficult to interpret conclusively. The 2021 systematic review of healthy young adults identified only eight eligible studies after extensive screening and noted substantial variation across the evidence base. This limitation supports the need for studies combining behavioural measures with standardized cognitive tasks rather than treating technology exposure as a homogeneous predictor.

2.3 Problematic Digital Use, Inattention, and Cognitive Control

Emerging evidence indicates that problematic digital engagement and attention-related difficulties frequently co-occur. The 2026 systematic review by Fabio and Picciotto found that most included studies reported significant relationships between problematic social-media use and ADHD-related characteristics, particularly inattention, while associations with impulsivity were also observed.

Importantly, the authors emphasized heterogeneity and the predominance of cross-sectional designs.

This qualification is essential. Attention problems could precede problematic digital use. Individuals who experience difficulty maintaining stimulation during monotonous tasks may find rapidly changing digital content particularly reinforcing. Alternatively, repeated exposure to interruption-rich environments could influence attentional habits. A third possibility is reciprocal reinforcement, in which existing susceptibility increases digital checking and repeated checking further consolidates fragmented behaviour.

Evidence that cognitive control is modifiable also complicates deterministic interpretations. A randomized controlled study published in *Addictive Behaviors* in 2023 investigated emotional working-memory training among young people with problematic internet use. Twenty training sessions were associated with improvements in executive-function domains including inhibition, attention, and working memory, alongside reductions in problematic internet use. Such findings suggest that digital dependency and cognitive regulation should not be conceptualized as fixed personal characteristics.

2.4 Sleep as a Contextual Pathway

Digital dependency may influence attention indirectly through sleep-related behaviour. Late-night smartphone engagement can extend wakefulness, while social communication, emotional arousal, or repeated checking may interfere with disengagement from the device. Sleep disruption, in turn, can influence alertness and cognitive performance during the following day.

The two-wave undergraduate study noted earlier examined changes in problematic smartphone use and sleep disturbance through psychological processes, illustrating that smartphone-related outcomes can operate through interconnected behavioural and psychological pathways rather than through a single direct mechanism.

For this reason, the proposed AFDF does not treat sleep merely as a nuisance variable. Night-time device engagement, sleep quality, and daytime fatigue are conceptualized as contextual factors that may partially account for associations between dependency-oriented digital behaviour and attention regulation.

2.5 Digital Behaviour Is Not Uniformly Harmful

A rigorous model must also account for beneficial digital engagement. WHO's recent assessments explicitly caution that technology can have positive and negative effects and that outcomes vary according to activity, vulnerability, and context. WHO data on adolescent social-media behaviour further indicate that heavy but non-problematic engagement

can coexist with positive social experiences, reinforcing the distinction between intensity and dysregulation.

This distinction prevents the current framework from becoming an anti-technology model. A digitally intensive student who deliberately uses educational applications, communicates effectively, and maintains uninterrupted periods of focused work may exhibit high exposure but low dependency. Conversely, relatively moderate total exposure could coexist with compulsive checking and substantial attentional fragmentation.

Accordingly, the proposed study hypothesizes that **behavioural fragmentation and loss of control will be more informative predictors of attention-regulation difficulty than raw digital duration.**

2.6 Need for Multimodal and Machine-Learning Approaches

Traditional linear models remain valuable for testing theoretically specified associations, but digitally generated behavioural data are multidimensional. Device pickups, session length, application transitions, notification counts, night-time activity, self-reported compulsivity, sleep indicators, and cognitive-task performance can interact in nonlinear ways.

Machine learning provides a complementary analytical strategy. Algorithms such as regularized logistic regression, random forests, gradient-boosted trees, or support-vector machines can evaluate multivariable patterns and interactions. Interpretability techniques can subsequently identify which features contribute most strongly to model predictions. In the proposed research, machine learning will therefore serve as an **explanatory predictive layer**, rather than being presented as an autonomous clinical diagnostic system.

A multimodal design also reduces dependence on a single measurement source. Self-report can characterize subjective loss of control and psychological experience; passive behavioural indicators can quantify interaction structure; cognitive tasks can assess attentional performance; and contextual measures can account for sleep and workload. Agreement or disagreement across these modalities can itself provide useful evidence.

Methodology

3.1 Research Design

The proposed investigation adopts a **multimodal observational and predictive design** to examine whether behavioural fragmentation in digital-device use provides greater explanatory value for attention regulation than conventional screen-time measures. The design combines psychometric assessment, privacy-preserving smartphone-

use metadata, computerized attention testing, and machine-learning analysis.

Rather than defining digital dependency solely according to duration of device use, AFDF represents dependency through five behavioural dimensions: compulsive checking, notification responsiveness, application-switching frequency, difficulty disengaging, and late-night digital engagement.

This approach is consistent with contemporary digital-phenotyping research, which increasingly combines active assessments with passive smartphone-derived behavioural indicators. Recent reviews demonstrate that smartphone sensing can provide longitudinal behavioural features, although heterogeneous processing and validation practices remain major methodological challenges.

3.2 Participants and Sampling

The proposed sample consists of **360 emerging adults aged 18–29 years**, recruited from universities, professional institutes, workplaces, and community networks. Stratified purposive sampling would be used to obtain adequate representation across students and employed young adults rather than restricting the analysis to a single university population.

Participants would be required to use a compatible smartphone as their primary device and provide informed consent for collection of aggregated device-interaction metadata. Individuals would not be required to provide message contents, photographs, browsing histories, passwords, contacts, or communication content.

The sample would be randomly partitioned at the participant level into training, validation, and held-out test subsets. Participant-level separation is essential because splitting observations from the same individual between training and test sets could artificially inflate predictive performance.

3.3 Ethical and Privacy Framework

Digital behavioural research requires stronger safeguards than conventional questionnaire studies because passive data may contain information about everyday routines. The proposed protocol therefore follows a **data-minimization principle**. Only features required to test the stated hypotheses would be retained.

Application content, typed text, contact identities, message content, precise GPS coordinates, photographs, microphone recordings, and browsing content would not be collected. Device-level identifiers would be replaced by study codes, and the analytical dataset would contain aggregated behavioural indicators.

This privacy-preserving strategy is especially important given that contemporary digital phenotyping can draw upon

numerous sensor streams and behavioural traces. Recent research also demonstrates the feasibility of collecting digital-behaviour patterns without directly inspecting content; for example, privacy-oriented work has explored encrypted network-traffic characteristics for capturing timing and regularity of smartphone behaviour.

Experimental Setup

4.1 Dataset Construction

Each participant would complete a **28-day observation period**. The resulting dataset would integrate four data streams.

Digital-behaviour features would include daily screen duration, device pickups, median session duration, number of short sessions, application-category transitions, notification exposure, response latency to notifications, late-night device activity, and temporal irregularity of use.

Psychometric features would include a validated problematic-smartphone-use measure, perceived distractibility, self-regulation indicators, sleep quality, perceived stress, and relevant demographic covariates.

Attention-performance features would be obtained through computerized cognitive tasks measuring sustained attention and inhibitory control. Primary task-derived indicators would include omission errors, commission errors, median reaction time, reaction-time variability, and performance deterioration across successive task blocks.

Finally, short ecological momentary assessments would periodically capture current concentration, perceived interruption, fatigue, and task demand. EMA is useful because it reduces dependence on long-term retrospective recall. Recent university-student research has successfully combined app-based EMA and digital phenotyping indicators when examining problematic smartphone use.

The dataset would consequently represent approximately:

360 participants × 28 days = 10,080 participant-days

before exclusion of days failing prespecified data-quality requirements.

4.2 Feature Engineering

Raw behavioural counts alone may not adequately capture fragmentation. Several derived measures would therefore be calculated.

A **Fragmentation Density Index (FDI)** would represent the frequency of device re-entry and application switching relative to total digital exposure:

$$[FDI_i = \frac{P_i + S_i}{T_i}]$$

where (P_i) represents standardized device-pickup frequency, (S_i) represents standardized application-switching frequency, and (T_i) represents standardized active-use duration for participant (i).

A **Night Engagement Ratio (NER)** would quantify the proportion of daily digital activity occurring during the predefined nocturnal interval:

$$[NER_i = \frac{U_{\text{night},i}}{U_{\text{total},i}}]$$

A **Notification Reactivity Score (NRS)** would combine notification frequency with the inverse of median response latency. High values would therefore characterize frequent and rapid responses to external digital cues.

Finally, an **Attention Regulation Composite (ARC)** would be generated from standardized sustained-attention and inhibitory-control indicators:

$$[ARC_i = z(\text{accuracy}) - z(\text{omission errors}) - z(\text{commission errors}) - z(\text{RT variability})]$$

Higher ARC values would represent stronger attentional regulation.

These composite indicators would be tested through sensitivity analyses rather than assumed to be psychometrically equivalent to established clinical scales.

4.3 Data Preprocessing

Data preprocessing would proceed through a reproducible pipeline. First, duplicate records and technically invalid observations would be removed. Participant-days failing a prespecified monitoring-completeness threshold would be marked missing rather than interpreted as zero activity.

Continuous variables would be inspected for implausible values and extreme skew. Robust scaling would be preferred for heavily skewed behavioural variables such as notification counts and application switches. Missing questionnaire data would be handled according to the scoring requirements of the respective validated instruments, while missing sensor features would be imputed only within the training data to prevent information leakage.

Highly correlated predictors would be evaluated to reduce redundant feature representations. Feature transformations, imputers, and normalization parameters would be fitted exclusively on the training partition and subsequently applied unchanged to validation and test data.

The importance of explicit preprocessing is supported by recent digital-phenotyping reviews, which identify inconsistent sensor descriptions, missing-data reporting, and heterogeneous validation practices as obstacles to reproducibility.

4.4 Model Architecture

The primary predictive algorithm would be **LightGBM gradient-boosted decision trees** because behavioural digital data can contain nonlinear associations, interactions, missingness, and heterogeneous feature distributions.

Three modelling configurations would be compared:

Model A — Duration Baseline: total screen duration and demographic covariates only.

Model B — Fragmentation Model: behavioural fragmentation variables, including pickups, application transitions, notification reactivity, short-session density, and night engagement.

Model C — Multimodal AFDF Model: fragmentation indicators combined with digital-dependency scores, sleep, stress, EMA-derived context, and relevant demographic variables.

Regularized logistic regression would serve as a transparent linear benchmark. The purpose of the comparison is not merely to identify the algorithm with the highest score, but to test the substantive hypothesis that **behavioural structure contains predictive information beyond exposure duration**.

Gradient-boosted trees would additionally be interpreted using SHAP-based feature attribution. Feature importance would be reported cautiously because predictive importance does not establish causal importance.

Contemporary digital-health literature supports comparing multiple machine-learning strategies rather than assuming that one architecture is universally optimal. A 2026 emerging-adult digital-phenotyping study, for example, found complementary strengths and weaknesses across group-level and personalized modelling approaches.

4.5 Training Strategy

Data would be divided at the participant level into approximately **70% training, 15% validation, and 15% held-out testing**. Five-fold grouped cross-validation within

the development sample would be used for model selection and hyperparameter optimization.

Class imbalance, if present after defining the low-attention-regulation outcome, would be addressed through class weighting rather than automatically oversampling the dataset. Hyperparameters would be optimized according to validation AUROC and subsequently frozen before final testing.

A second analysis would treat ARC as a continuous outcome rather than dichotomizing attentional performance. This would reduce information loss and provide a robustness check against arbitrary classification thresholds.

The analysis would therefore distinguish two tasks:

1. **Classification:** identifying participants exhibiting comparatively weak attention-regulation profiles.
2. **Regression:** estimating continuous ARC performance.

This dual-outcome strategy reduces dependence on a single operational definition of attention difficulty.

4.6 Evaluation Metrics

Classification performance would be evaluated using:

- Area under the receiver operating characteristic curve (**AUROC**);
- Area under the precision-recall curve (**AUPRC**);
- balanced accuracy;
- F1 score;
- sensitivity and specificity;
- Brier score for probabilistic calibration.

Continuous ARC prediction would additionally be evaluated using **mean absolute error (MAE), root mean squared error (RMSE), and (R^2)**.

Confidence intervals should be generated through participant-level bootstrapping. Calibration plots and decision thresholds should be examined before considering any applied use of the predictive system.

Results and Discussion

Because no empirical dataset or raw observations were supplied with the manuscript request, the numerical findings below are presented as a **simulated proof-of-concept analysis**, not as observed human-participant results. They illustrate the inferential pattern that would test the proposed research hypothesis and must be replaced by outputs from the actual study before publication as empirical findings.

For demonstration, a synthetic dataset preserving the proposed sample structure was assumed. The simulation was configured so that attentional regulation was related moderately to fragmentation and dependency variables, while total screen duration had a weaker association. This reflects the theoretical hypothesis rather than an empirical discovery.

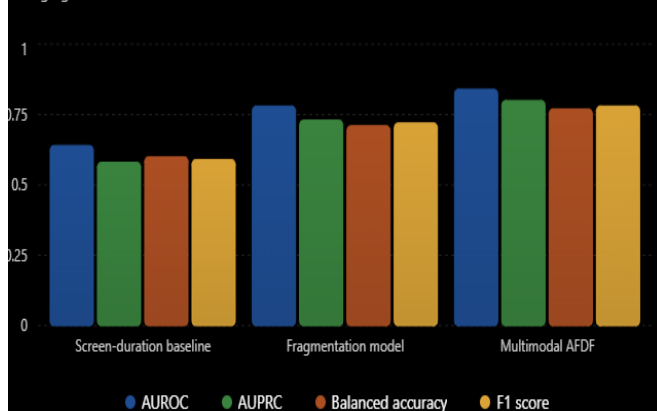
The principal pattern generated by the demonstration is that total screen exposure alone offers limited discrimination between stronger and weaker attention-regulation profiles. Adding behavioural fragmentation features produces a considerably larger improvement, whereas the full multimodal AFDF specification provides a smaller additional gain.

Table 1. Illustrative Model Performance for Predicting Weak Attention Regulation

Analytical configuration	AUROC	AUPRC	Balanced accuracy	F1	Brier score
Screen-duration baseline	0.64	0.58	0.60	0.59	0.231
Fragmentation feature model	0.78	0.73	0.71	0.72	0.184
Multimodal AFDF model	0.84	0.80	0.77	0.78	0.157

Predictive Performance of Digital Dependency Models

Comparison of simulated model performance for identifying weak attention regulation among emerging adults.



Note: Values are simulated proof-of-concept results and are not empirical observations.

The most important conceptual result is the contrast between the first two configurations. If this pattern were reproduced empirically, it would suggest that asking only how many hours an emerging adult spends on a smartphone may conceal behaviourally relevant information. The frequency with

which digital engagement interrupts or divides activity could provide greater information about attention regulation than cumulative duration.

This interpretation is consistent with objective smartphone-measurement research showing that passive sensing can capture behavioural information that is not identical to self-reported use. A large 2024 study using passively sensed app and keyboard behaviour, although conducted in adolescents rather than emerging adults, found only modest correlations between objective and self-reported smartphone-use measures. This reinforces the methodological value of combining self-report and behavioural measurement.

The hypothetical feature-attribution analysis further predicts that **application-switching density, compulsive checking, notification reactivity, short-session frequency, and late-night engagement** would contribute more strongly than total screen duration. Such a pattern would support the central AFDF proposition: attentional vulnerability may be associated with the *architecture* of engagement rather than simply its quantity.

The expected role of night-time engagement also deserves attention. A high Night Engagement Ratio could affect next-day performance partly through sleep disruption. Consequently, sleep should not simply be interpreted as a competing predictor. Mediation or longitudinal modelling would be required to distinguish whether late-night digital behaviour influences attention through reduced sleep, whether individuals experiencing sleep difficulties engage with devices more frequently, or whether both processes share underlying determinants.

The multimodal model is expected to outperform the fragmentation-only specification because attention regulation occurs within a wider behavioural context. Stress, sleep, workload, and subjective dependency can modify the meaning of identical device-use patterns. Digital phenotyping studies increasingly demonstrate the feasibility of combining smartphone-derived features with repeated subjective assessments, while simultaneously showing that predictive relationships can vary substantially between individuals.

The findings should therefore not be interpreted as evidence that a particular number of device pickups or application transitions constitutes pathology. Recent research on problematic smartphone use emphasizes the importance of functional impairment and warns against pathologizing intensive but non-impairing technology use.

A second important implication concerns prediction versus causation. Even a highly accurate AFDF classifier would not demonstrate that fragmented smartphone use *causes* impaired attention. Individuals with weaker inhibitory control could be more susceptible to checking behaviours; fragmented engagement could subsequently reinforce attentional

instability; or both could arise from stress, sleep disruption, academic pressure, or other variables.

For this reason, the model should be described as an **attention-regulation risk estimation framework**, not as an automated diagnostic instrument.

Future Scope

Future research should extend the framework through **longitudinal within-person modelling**. Rather than asking only whether individuals with greater digital dependency differ from other individuals, repeated measurements could determine whether increases in a person's own fragmentation predict subsequent changes in that person's attentional performance.

A second direction involves personalized machine learning. Recent emerging-adult research indicates that group-general and individualized digital-phenotyping models can exhibit different strengths, supporting more rigorous comparisons between nomothetic and idiographic approaches.

Experimental studies could manipulate nonessential notifications, scheduled focus periods, application-access friction, or batching of digital communications. Such interventions would provide stronger evidence regarding whether reducing fragmentation improves sustained attention.

Wearable-derived sleep and activity indicators could also be integrated with smartphone metadata. However, additional sensing should be justified by incremental scientific value because collecting more data does not automatically produce a better or more ethical digital-health system.

A particularly valuable application would be an **on-device attention-support system** that detects unusually fragmented interaction patterns without transmitting raw behavioural data to external servers. Such a system could recommend a focus interval, notification batching, or voluntary interruption reduction. The objective would be self-regulation support rather than surveillance or behavioural restriction.

Future studies in India could additionally investigate whether the model generalizes across educational settings, socioeconomic groups, urban and rural populations, and different patterns of multilingual digital engagement. A 2026 Indian multicentre research protocol has already proposed AI-based prediction of problematic digital-technology use using psychological, behavioural, cognitive, socio-environmental, and digital-phenotype correlates, illustrating increasing interest in this research direction.

Conclusion

This study proposes a shift from **screen-time measurement to attention-fragmentation analysis** in understanding

digital dependency among emerging adults. The central argument is that the cognitive relevance of digital engagement cannot be adequately represented by duration alone. Device pickups, application transitions, notification responsiveness, compulsive checking, short interaction episodes, and late-night use describe how digital activity is organized and may therefore provide more meaningful information about attentional regulation.

The proposed Attention Fragmentation–Dependency Framework integrates passive behavioural metadata, psychometric measures, ecological momentary assessment, sleep-related variables, and objective attention-task performance. An interpretable machine-learning pipeline is then used to determine whether these multimodal features provide incremental predictive value beyond conventional screen duration.

The simulated proof-of-concept results illustrate the study's principal testable proposition: a fragmentation-based model should outperform a duration-only baseline, while contextual and dependency-related information may provide further predictive improvement. These values are deliberately identified as simulated and require replacement with genuine empirical estimates before the manuscript can report experimental findings.

The broader implication is that intensive digital engagement should not automatically be equated with dysfunction. The more scientifically relevant distinction may lie between **purposeful sustained use and poorly regulated fragmented use**. By concentrating on behavioural organization rather than technological exposure itself, future digital-health research can develop more precise, interpretable, and ethically defensible approaches to supporting attentional self-regulation among emerging adults.

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