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Digital neurobehavioral signature and its association with cognitive function and psychological resilience: a cross-sectional study of digital lifestyle patterns and cognitive health

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Abstract

Aim: To investigate the associations between the digital neurobehavioral signature (DNS) score, cognitive function, and psychological resilience among adults, and to explore the potential mediating role of psychological resilience in the association between digital behavioral patterns and cognitive performance.

Methods: A cross-sectional study was conducted at Abbasi Shaheed Hospital, Karachi, among 400 adults. DNS was assessed using a composite DNS score derived from screen time, sleep, physical activity, and digital engagement. Cognitive function was measured using the Montreal Cognitive Assessment, while psychological resilience and depressive symptoms were assessed using validated scales. Multivariable regression and mediation analyses were performed to evaluate independent associations and indirect effects. For continuous outcomes, differences across DNS profiles were assessed using one-way ANOVA, followed by Bonferroni-adjusted post-hoc pairwise comparisons when the ANOVA was significant. A $p < 0.05$ was considered statistically significant.

Results: Participants with maladaptive DNS demonstrated significantly lower cognitive performance and psychological resilience compared with those with adaptive profiles, with significant differences confirmed by Bonferroni-adjusted post-hoc pairwise comparisons ($p < 0.001$). Higher DNS composite scores were independently associated with lower cognitive scores ($\beta = -0.34$, $p < 0.001$). Psychological resilience was positively associated with cognitive function and partially mediated the association between digital behavioral patterns and cognition.

Conclusions: These findings suggest that the exploratory DNS composite behavioral index is associated with cognitive function and psychological resilience and may provide a framework for investigating relationships between digital lifestyle behaviors and neurocognitive and psychological outcomes.

Keywords

digital neurobehavioral signature, cognitive function, psychological resilience, digital phenotyping, neuroprotection, behavioral biomarkers

Introduction

Neurodegenerative disorders and cognitive impairment constitute a growing global health concern, driven by demographic transitions, increased life expectancy, and complex interactions between biological and environmental determinants [1]. While advances in molecular neuroscience have significantly enhanced understanding of disease mechanisms, translation into effective preventive strategies remains limited [2]. Consequently, there is increasing emphasis on identifying scalable, non-invasive behavioral measures that may help characterize factors associated with adverse cognitive and psychological outcomes at an earlier stage [3].

In recent years, the widespread adoption of digital technologies has fundamentally altered human behavior, generating continuous streams of data that reflect real-world patterns of activity, sleep, and social interaction [4]. This has led to the emergence of digital phenotyping, which enables the quantification of behavioral signatures through data derived from personal digital devices [5]. The digital neurobehavioral signature (DNS) was conceptualized as a composite behavioral construct incorporating screen exposure, sleep behavior, physical activity, and digital engagement, domains that may be relevant to brain health [6–10].

Behavioral domains incorporated into the DNS framework were selected because they represent key components of contemporary digital lifestyles and have consistently demonstrated associations with cognitive and psychological health outcomes [7]. Screen exposure, sleep behavior, physical activity, and patterns of digital engagement are not only measurable through digital technologies but also constitute modifiable behavioral factors that may influence brain health across the lifespan [8]. Previous research has shown that each of these domains independently influences cognitive performance, emotional well-being, and mental health outcomes [9, 10]. Importantly, these behaviors frequently coexist and interact in real-world settings; therefore, combining them into a composite DNS may provide a more comprehensive representation of cumulative behavioral risk and protective factors than examining individual exposures in isolation.

Accumulating evidence indicates that these behavioral domains are closely associated with cognitive functioning. Excessive or inadequately regulated screen exposure has been linked to less favorable outcomes in attention, executive functioning, and other domains of cognitive development, whereas regular physical activity and healthy sleep patterns are generally associated with more favorable cognitive and educational outcomes [11, 12]. Importantly, the relationship between digital behavior and cognition appears to be context-dependent, with active and purposeful engagement potentially exerting protective effects, while passive and excessive use may contribute to cognitive vulnerability [13].

Despite these insights, existing research remains largely reductionist, focusing on individual behavioral factors rather than integrated patterns that more accurately reflect real-world exposures. The concept of DNS provides a more comprehensive framework by capturing the cumulative and interactive effects of multiple behavioral domains. However, empirical investigations adopting this integrative approach remain scarce, particularly in low- and middle-income settings where digital ecosystems and health determinants differ substantially from high-income contexts [10, 14].

While the term DNS has been used in other contexts to describe digital biomarker platforms based on passive sensor data, wearable technologies, or machine-learning-driven behavioral profiling [15], the DNS proposed in the present study represents a distinct conceptual construct. Specifically, it refers to a composite behavioral index derived from self-reported measures of screen exposure, sleep behavior, physical activity, and digital engagement. The DNS was developed as an exploratory framework to capture integrated digital lifestyle patterns and their potential associations with cognitive function and psychological resilience. Accordingly, it should not be interpreted as a validated digital biomarker; rather, it represents a study-specific composite behavioral construct intended to facilitate hypothesis generation and exploratory investigation of digitally mediated behavioral influences on brain health.

Psychological resilience represents an important psychological factor that may influence cognitive health and adaptation to behavioral and environmental stressors. Defined as the process of negotiating, managing, and adapting to significant sources of stress or trauma, it represents a relevant dimension within the neuroprotection paradigm. Research indicates that resilience may help mitigate the physical and emotional distress associated with chronic illnesses, including neurodegenerative diseases [16]. It may function as a key intermediary linking behavioral exposures to cognitive health, yet its role within digitally mediated behavioral frameworks has not been adequately explored.

The present study aimed to address these gaps by examining the association between DNS, cognitive function, and psychological resilience in an adult population. By integrating behavioral, cognitive, and psychological domains within a unified analytical model, this study sought to improve understanding of how digital behavioral patterns relate to cognitive and psychological outcomes in real-world settings.

Research questions and hypotheses

Research questions

The study was guided by the following research questions:

1. Is there an association between digital neurobehavioral signature and cognitive function among adults?
2. Is there an association between digital neurobehavioral signature and psychological resilience among adults?
3. What is the relationship between psychological resilience and cognitive function?
4. Does psychological resilience mediate or partially explain the relationship between digital neurobehavioral signature and cognitive function?

Hypotheses

Based on existing theoretical and empirical evidence, the following hypotheses were formulated:

H1: Individuals exhibiting a more maladaptive digital neurobehavioral signature will demonstrate significantly lower cognitive function scores.

H2: Individuals exhibiting a more maladaptive digital neurobehavioral signature will demonstrate significantly lower psychological resilience scores.

H3: Higher levels of psychological resilience will be positively associated with better cognitive function.

H4: Psychological resilience will partially mediate the association between digital neurobehavioral signature and cognitive function, such that maladaptive digital behavioral patterns will be associated with reduced resilience, which in turn will be associated with poorer cognitive performance.

Materials and methods

Study design and setting

A cross-sectional analytical study was conducted at the outpatient department (OPD) at Abbasi Shaheed Hospital, Karachi, Pakistan. Ethical approval for the study was obtained prior to data collection from the Ethics Review Committee of Center for Integrated Health Research and Innovation (CIHRI) (Reference No: MS/ERC/029/2025; Date: 01 March 2025). The hospital provides multidisciplinary outpatient services, including neurology, general medicine, and psychiatry clinics, making it an appropriate setting for recruiting participants with varied digital exposure patterns and cognitive profiles.

The study was carried out over a five-month period from 14 March 2025 to 14 August 2025, and was designed in accordance with the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines to ensure methodological rigor, transparency, and reproducibility.

Study population

The study population included adults aged 18–65 years who were able to communicate effectively, provide informed consent, and complete all study assessments, including questionnaires and cognitive testing. Participants were recruited from OPDs, accompanying attendants, and community visitors attending the hospital during the study period. Individuals with previously diagnosed major neurocognitive disorders, dementia, severe psychiatric illness requiring hospitalization, significant neurological deficits affecting cognitive assessment, acute medical illness at the time of enrollment, severe sensory impairment, or inability to complete study procedures were excluded.

Sample size and sampling technique

Sample size was determined using a standard single-proportion cross-sectional formula, assuming a 50% prevalence of altered cognitive performance associated with behavioral risk exposure, a 95% confidence interval, and a 5% margin of error. The minimum required sample size was calculated to be 384 participants. To enhance statistical robustness and compensate for potential incomplete responses, the final sample size was increased to 400 participants. A non-probability consecutive sampling technique was employed, whereby all eligible individuals presenting during the data collection period were approached sequentially until the target sample size was achieved after obtaining informed consent. A total of 427 individuals were initially approached. Twenty-seven individuals were excluded prior to final analysis. Of these, 11 did not meet eligibility criteria, while 16 had incomplete responses. An incomplete response was defined as failure to complete one or more primary study measures, including the DNS assessment items, Montreal Cognitive Assessment (MoCA) evaluation, Connor-Davidson Resilience Scale (CD-RISC) questionnaire, Patient Health Questionnaire-9 (PHQ-9) questionnaire, or key sociodemographic variables required for multivariable analysis. Only participants with complete datasets were included in the final analysis.

Study variables and operational definitions

The primary exposure variable in this study was the DNS, conceptualized as a study-specific composite representation of daily behavioral patterns related to digital technology use and lifestyle routines [17].

DNS was developed as an exploratory composite behavioral index intended to capture multiple dimensions of digital lifestyle behavior within a single summary measure. The four selected domains (screen exposure, sleep behavior, physical activity, and digital engagement type) were chosen based on previous literature reporting associations between these behavioral domains and cognitive or psychological outcomes [18–20]. Because no established composite instrument incorporating all four domains currently exists, equal weighting was applied to each component to ensure methodological simplicity and transparency and to avoid introducing arbitrary differential weighting in the absence of empirical evidence supporting the relative importance of individual domains. The scoring framework was designed to represent cumulative behavioral risk rather than to serve as a validated diagnostic or predictive instrument. To address reproducibility and methodological transparency, this construct was

operationalized as a composite DNS score derived from four predefined behavioral domains: screen exposure duration, sleep timing and regularity, physical activity patterns, and type of digital engagement. Each domain was quantified using a standardized three-point ordinal scoring system (0–2), where higher scores indicated more maladaptive behavior.

Screen exposure duration was assessed based on self-reported average daily screen time (including smartphones, computers, and television) and categorized as ≤ 2 hours/day (0 points), > 2 to ≤ 5 hours/day (1 point), and > 5 hours/day (2 points). Sleep timing and regularity were evaluated using self-reported sleep duration and consistency of sleep-wake cycles and classified as regular sleep (7–9 hours/night with consistent timing = 0 points), mildly irregular sleep (> 6 to < 7 hours/night or variable timing = 1 point), and poor sleep (≤ 6 hours/night, irregular timing, or frequent disturbances = 2 points). Physical activity patterns were measured based on weekly duration of moderate-to-vigorous activity and categorized as ≥ 150 minutes/week (0 points), 60–149 minutes/week (1 point), and < 60 minutes/week (2 points). Digital engagement type was classified based on predominant usage behavior into active/goal-directed use (e.g., educational or occupational activities = 0 points), mixed use (1 point), and passive consumption (e.g., social media scrolling or streaming = 2 points).

A composite DNS score was calculated by summing all domain scores (range: 0–8), with higher scores reflecting more maladaptive behavioral patterns. Classification thresholds were established a priori for descriptive and analytical purposes, whereby scores of 0–2 represented adaptive behavioral profiles, scores of 3–5 represented intermediate profiles, and scores of 6–8 represented maladaptive profiles. These thresholds were selected to facilitate risk stratification across increasing levels of behavioral burden and were not derived from external validation studies. Consequently, the DNS categories should be interpreted as exploratory groupings developed for the present investigation rather than clinically validated classifications.

Since the DNS represents a study-specific composite behavioral construct, formal psychometric validation, predictive performance assessment, calibration analysis, and external validation were beyond the scope of the present study and warrant investigation in future research.

The primary outcome variable was cognitive function, assessed using the MoCA, a widely validated screening instrument for global cognitive performance [21]. The MoCA evaluates multiple cognitive domains, including attention, executive function, memory, language, visuospatial ability, and orientation, with higher scores reflecting better cognitive functioning.

Psychological resilience was considered a key secondary outcome and potential mediator, conceptualized as the ability to maintain or regain psychological well-being in the face of stressors. It was assessed using the CD-RISC [22], which provides a standardized measure of resilience capacity across emotional, cognitive, and behavioral domains.

Depressive symptoms were measured as a key covariate using the PHQ-9 [23], given its known influence on both cognitive performance and behavioral patterns.

All psychometric instruments (MoCA, CD-RISC, and PHQ-9) were administered in their validated versions, and standardized scoring procedures were followed according to established guidelines. Moreover, sociodemographic and clinical variables, including age, gender, education level, occupation, socioeconomic status, and chronic comorbid conditions such as diabetes and hypertension, were recorded to control for potential confounding effects in the final analysis.

Data collection procedure

Data collection was conducted through a structured, interviewer-administered questionnaire to ensure clarity, reduce missing data, and accommodate participants with varying levels of literacy. Trained research assistants approached eligible individuals in outpatient waiting areas and explained the study objectives in detail before obtaining informed consent. Interviews were conducted in a private and quiet setting within the hospital to ensure confidentiality and minimize response bias. Each participant underwent a

standardized assessment sequence, beginning with sociodemographic data collection, followed by evaluation of digital neurobehavioral patterns, cognitive assessment using MoCA, and psychological assessment using validated scales. The average duration of each interview was approximately 20 to 25 minutes. To ensure data quality and consistency, all research assistants received prior training, and periodic supervision was conducted. Completed questionnaires were reviewed daily for completeness and accuracy, and double data entry was performed to minimize entry errors.

Statistical analysis

Data were entered and analyzed using SPSS version 26. Continuous variables were summarized as means and standard deviations, while categorical variables were presented as frequencies and percentages. Initial comparisons between groups were performed using independent sample *t*-tests and one-way analysis of variance (ANOVA), as appropriate, to explore differences in cognitive function and psychological resilience across digital behavioral categories. When the ANOVA was statistically significant, Bonferroni-adjusted post-hoc pairwise comparisons were performed to identify specific between-group differences. Pearson correlation analysis was used to examine bivariate relationships among continuous variables. For these analyses, screen time was entered as self-reported average daily screen exposure (hours/day) and sleep quality as the self-reported sleep duration and sleep-wake regularity measure described above, both treated as continuous variables. Normality of continuous variables was assessed using the Shapiro-Wilk test and visual inspection of histograms. Appropriate parametric or non-parametric tests were applied accordingly.

To determine independent associations, multivariable linear regression models were constructed with cognitive function as the dependent variable. DNS score was entered as the primary independent variable, while age, gender, education level, comorbidities, and depressive symptoms were included as covariates to adjust for confounding. Multicollinearity was assessed using the variance inflation factor (VIF), and model assumptions (linearity, homoscedasticity, and normality of residuals) were verified prior to interpretation. VIF values below 5 were considered indicative of acceptable multicollinearity. In the present analysis, VIF values ranged from 1.08 to 2.34, indicating no evidence of problematic multicollinearity among the predictors. Model assumptions were assessed through examination of standardized residual plots, normal probability (Q-Q) plots, residual-versus-fitted value plots, and tests of homoscedasticity, which demonstrated acceptable linearity, homoscedasticity, and approximate normal distribution of residuals. Residual independence was evaluated using the Durbin-Watson statistic (1.92), indicating acceptable independence of residuals. Regression results are reported using standardized beta coefficients (β) to facilitate comparison of the relative strength of associations across predictors measured on different scales. Standard errors (SE), *t*-values, and *p*-values correspond to the unstandardized regression coefficients (B). Psychological resilience was subsequently evaluated as a potential mediating variable using bootstrapped mediation analysis with 5,000 resamples, allowing estimation of indirect effects with greater statistical reliability. Because all study variables were measured at a single time point, the mediation analysis was conducted to explore potential indirect associations rather than establish causal pathways. The temporal ordering assumed in the mediation model was based on theoretical considerations and prior literature; however, alternative causal directions remain possible, and the findings should therefore be interpreted as exploratory. A *p*-value of less than 0.05 was considered statistically significant.

The objective of the present study was to examine cross-sectional associations between digital behavioral patterns, psychological resilience, and cognitive function rather than to develop, validate, or evaluate the predictive performance of a clinical prediction model. Therefore, assessments of model discrimination, calibration, predictive accuracy, or external validation were not performed. Future longitudinal studies involving independent populations are warranted to evaluate the psychometric properties, predictive validity, and generalizability of the DNS framework.

Results

Sociodemographic and clinical characteristics

The study included 400 participants with a mean age of 39.6 ± 12.41 years, representing a relatively young to middle-aged adult population. Males constituted 53.50% (*n* = 214) of the sample, while females accounted for 46.50% (*n* = 186). As shown in Table 1, educational attainment was relatively balanced, with 40.00% of participants having graduate-level education or higher, indicating variation in educational attainment within the study population. Regarding clinical comorbidities, 28.00% had hypertension and 24.00% had diabetes mellitus, reflecting the distribution of chronic diseases in the study population. Overall, the sociodemographic distribution indicated a heterogeneous sample suitable for evaluating behavioral and cognitive associations across diverse participant characteristics.

Table 1. Sociodemographic and clinical characteristics of participants (*n* = 400).

Variable	Category	Frequency (*n*)	Percentage (%)
Age (years)	Mean ± SD	39.6 ± 12.41	-
Gender	Male	214	53.50
	Female	186	46.50
Education level	Primary	78	19.50
	Secondary	162	40.50
	Graduate or higher	160	40.00
Socioeconomic status	Low	148	37.00
	Middle	184	46.00
	High	68	17.00
Hypertension	Yes	112	28.00
Diabetes mellitus	Yes	96	24.00

SD: standard deviation.

Distribution of DNS

The classification of participants into digital neurobehavioral profiles was based on the composite DNS score (range: 0–8), derived from four domains: screen exposure duration, sleep timing and regularity, physical activity patterns, and digital engagement type, as described in the Methods section. Participants were categorized into adaptive (score 0–2), intermediate (score 3–5), and maladaptive (score 6–8) profiles using predefined thresholds. The distribution of digital neurobehavioral profiles revealed that 35.50% (*n* = 142) of participants were classified as adaptive, 42.00% (*n* = 168) as intermediate, and 22.50% (*n* = 90) as maladaptive. Participants in the maladaptive category had higher cumulative DNS scores, reflecting a greater burden of adverse behavioral characteristics across the assessed domains, including prolonged screen exposure, irregular or insufficient sleep, low physical activity, and predominantly passive digital engagement. In contrast, the adaptive group demonstrated lower DNS scores, characterized by balanced digital usage, regular sleep patterns, and adequate physical activity levels. This distribution indicated that nearly two-thirds of participants were classified within the intermediate or maladaptive categories according to the exploratory DNS scoring framework, reflecting a greater cumulative burden of the behavioral characteristics incorporated into the composite index (Table 2).

Table 2. Digital neurobehavioral signature (DNS) profile distribution.

Digital behavior profile	DNS score range	Operational definition	Frequency (*n*)	Percentage (%)
Adaptive profile	**0–2**	Lower-burden behavioral profile characterized by relatively favorable patterns across the assessed domains	142	35.50
Intermediate profile	**3–5**	Intermediate-burden behavioral profile with partial imbalance across assessed domains	168	42.00
Maladaptive profile	**6–8**	Higher-burden behavioral profile characterized by multiple adverse behavioral characteristics across the assessed domains	90	22.50

Cognitive and psychological outcomes across digital profiles

As shown in Table 3, there was a clear graded decline in cognitive performance across digital neurobehavioral categories. Participants with adaptive digital behavior had the highest mean MoCA scores (27.2 ± 1.8), while those with maladaptive profiles demonstrated significantly lower scores (23.4 ± 2.9), with a statistically significant difference across groups ($p < 0.001$). Bonferroni-adjusted post-hoc pairwise comparisons were subsequently performed to identify differences between individual digital behavior profiles. A similar trend was observed for psychological resilience, which progressively decreased from adaptive to maladaptive groups. Conversely, depressive symptoms measured by PHQ-9 increased substantially across worsening digital behavior profiles. These findings indicated a graded cross-sectional association between digital behavioral patterns and cognitive and psychological outcomes. Although DNS categories demonstrated significant associations with cognitive performance and psychological resilience, these findings represented observed cross-sectional relationships and should not be interpreted as evidence of predictive validity or clinical utility.

Table 3. Cognitive and psychological outcomes across digital behavior profiles.

Outcome	Adaptive	Intermediate	Maladaptive	*p*-value
MoCA score (mean ± SD)	27.2 ± 1.8	25.6 ± 2.3	23.4 ± 2.9	< 0.001
Resilience (CD-RISC)	32.8 ± 5.1	29.4 ± 5.8	25.7 ± 6.2	< 0.001
PHQ-9 score	4.8 ± 2.1	7.6 ± 3.4	10.9 ± 4.2	< 0.001

MoCA: Montreal Cognitive Assessment; SD: standard deviation; CD-RISC: Connor-Davidson Resilience Scale; PHQ-9: Patient Health Questionnaire-9.

Correlation between study variables

The correlation analysis presented in Table 4 demonstrated significant interrelationships among digital behavior, cognition, and psychological variables. Cognitive function (MoCA scores) showed moderate positive correlations with psychological resilience ($r = 0.42$, $p < 0.01$) and sleep quality ($r = 0.44$, $p < 0.01$), while demonstrating significant negative correlations with depressive symptoms (PHQ-9; $r = −0.46$, $p < 0.05$) and screen time ($r = −0.39$, $p < 0.01$). Similarly, psychological resilience was positively associated with sleep quality ($r = 0.40$, $p < 0.01$) and inversely correlated with depressive symptoms ($r = −0.51$, $p < 0.01$) and screen time ($r = −0.33$, $p < 0.01$). Depressive symptoms were positively related to screen time ($r = 0.41$, $p < 0.01$) and negatively associated with sleep quality ($r = −0.48$, $p < 0.01$). Finally, screen time was inversely correlated with sleep quality ($r = −0.34$, $p < 0.001$). Taken together, these findings support the presence of a tightly interconnected pattern of associations, wherein maladaptive digital behaviors and less favorable sleep behavior are linked to diminished resilience and cognitive outcomes, while higher resilience was associated with lower depressive symptoms and better cognitive performance.

Table 4. Correlation matrix of key study variables.

Variable	MoCA	Resilience	PHQ-9	Screen time	Sleep quality
MoCA	1	0.42**	–0.46*	–0.39**	0.44**
Resilience	0.42**	1	–0.51**	–0.33**	0.40**
PHQ-9	–0.46*	–0.51**	1	0.41**	–0.48**
Screen time	–0.39**	–0.33**	0.41**	1	–0.34***
Sleep quality	0.44**	0.40**	–0.48**	–0.34***	1

*: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$. MoCA: Montreal Cognitive Assessment; PHQ-9: Patient Health Questionnaire-9.

Prior to conducting multivariable regression analyses, model assumptions were evaluated. Multicollinearity was assessed using the VIF, and all predictor variables demonstrated acceptable VIF values (< 5), suggesting no evidence of problematic multicollinearity. Assessment of standardized residual plots and probability plots suggested acceptable linearity and approximate normality of the residuals. Residual-versus-fitted value plots did not indicate substantial heteroscedasticity, and Durbin-Watson

statistics were consistent with acceptable independence of residuals. Overall, the diagnostic assessments supported the use of linear regression models for further analyses.

Factors associated with cognitive function

Multivariable regression analysis, shown in Table 5, revealed that the DNS score was independently associated with cognitive performance after adjusting for age, education, comorbidities, and depressive symptoms. Specifically, higher DNS scores were significantly associated with lower MoCA scores (β = −0.34, $p < 0.001$). Depressive symptoms were independently associated with lower cognitive performance, while higher educational attainment was associated with better cognitive performance. Older age was also independently associated with lower cognitive scores (β = −0.21, $p < 0.001$), whereas hypertension showed no significant independent association (β = −0.12, $p = 0.27$). The model explained 48% of the variance in cognitive function ($R^2 = 0.48$, $p < 0.001$), indicating substantial explanatory capacity of the included variables.

Table 5. Multivariable linear regression: factors associated with cognitive function (MoCA score).

Variables	β Coefficient	SE	*t*-value	*p*-value
Age	–0.21	0.04	–5.12	< 0.001
Education level	0.38	0.09	4.22	< 0.001
PHQ-9 score	–0.29	0.06	–4.83	< 0.001
Digital neurobehavioral score	–0.34	0.06	–5.71	< 0.001
Hypertension	–0.12	0.11	–1.09	0.27

Model $R^2 = 0.48$, $p < 0.001$. MoCA: Montreal Cognitive Assessment; PHQ-9: Patient Health Questionnaire-9; SE: standard errors.

Factors associated with psychological resilience

As shown in Table 6, psychological resilience was significantly associated with both behavioral and psychological factors. Higher depressive symptom scores were strongly associated with reduced resilience (β = −0.41, $p < 0.001$), while higher DNS scores were also independently associated with lower resilience levels (β = −0.28, $p < 0.001$). Education was positively associated with resilience, although the cross-sectional design precluded conclusions regarding a protective causal effect. Older age was associated with modestly lower resilience scores (β = −0.14, $p = 0.005$). The overall model explained 44% of the variance in resilience scores ($R^2 = 0.44$, $p < 0.001$).

Table 6. Multivariable regression: factors associated with psychological resilience.

Predictor	β Coefficient	SE	*t*-value	*p*-value
Age	–0.14	0.05	–2.80	0.005
Education	0.26	0.08	3.25	< 0.001
PHQ-9 score	–0.41	0.05	–8.20	< 0.001
Digital neurobehavioral score	–0.28	0.06	–4.67	< 0.001

Model $R^2 = 0.44$, $p < 0.001$. PHQ-9: Patient Health Questionnaire-9; SE: standard errors.

Mediation analysis: role of psychological resilience

Mediation analysis results, summarized in Table 7, indicated a statistically significant indirect association between DNS and cognitive function through psychological resilience. The total effect of digital behavior on cognition was significant (β = −0.34, $p < 0.001$), and remained significant after adjustment, although reduced in magnitude in the direct effect pathway (β = −0.25, $p < 0.001$). Importantly, the indirect association through psychological resilience was statistically significant (β = −0.09, $p = 0.01$), consistent with a statistically detectable indirect pathway in the cross-sectional data. These findings suggested that part of the observed association between maladaptive digital behavioral patterns and cognitive function may be statistically accounted for by differences in psychological resilience; however, the cross-sectional design precluded conclusions regarding temporal ordering or causal mechanisms.

Table 7. Mediation analysis: role of psychological resilience.

Pathway	Effect estimate	95% CI	*p*-value
Total effect (digital → cognition)	–0.34	–0.42 to –0.26	< 0.001
Direct effect	–0.25	–0.33 to –0.18	< 0.001
Indirect effect (via resilience)	–0.09	–0.15 to –0.03	0.01

Discussion

This study found that the exploratory DNS composite behavioral index was significantly associated with cognitive function and psychological resilience, suggesting that an integrated assessment of digital lifestyle behaviors may provide a potentially useful exploratory framework for investigating behavioral patterns associated with cognitive and psychological outcomes. However, the DNS developed in this study represents an exploratory composite behavioral construct derived from self-reported measures and should not be interpreted as a validated digital biomarker or clinical classification system. The observed graded relationship between maladaptive digital behaviors, such as excessive screen exposure, irregular sleep patterns, and reduced physical activity, and lower cognitive performance is broadly consistent with prior evidence linking excessive or disordered screen use to poorer attention and executive functioning, while disrupted sleep and reduced physical activity have also been associated with adverse cognitive outcomes [24, 25]. Similar associations have been reported in digital phenotyping research, where passively collected behavioral data derived from smartphone and device use have been associated with measures of mood, attention, and cognitive functioning [26]. It is important to distinguish the present DNS framework from previously described digital phenotyping approaches or digital biomarker platforms that utilize high-dimensional passive data, wearable sensors, smartphone-derived metrics, or machine-learning-based prediction models [27]. In contrast, the DNS used in this study was a questionnaire-based composite index developed to summarize multiple behavioral domains relevant to contemporary digital lifestyles. Therefore, the current findings should be considered hypothesis-generating, and no clinical or population-level application should be inferred until the construct has undergone appropriate psychometric, longitudinal, and external validation.

Importantly, this study extends the existing literature by integrating multiple behavioral domains into an exploratory neurobehavioral framework, thereby providing a comprehensive approach for examining associations between behavioral patterns and psychological outcomes [28, 29]. The statistically significant indirect association observed in the mediation analysis provides preliminary evidence that psychological resilience may account for part of the observed cross-sectional association between digital behavioral patterns and cognitive function. However, because all variables were measured at a single time point, the mediation findings cannot establish temporal relationships or causal mechanisms. The observed indirect association should therefore be interpreted cautiously, as alternative explanations, including reverse causality and unmeasured confounding, remain possible. The observed associations are broadly consistent with theoretical models of resilience suggesting that adaptive emotion regulation and coping processes may contribute to psychological adaptation and cognitive health [30, 31].

Furthermore, these results are consistent with evidence indicating that stress-related and psychosocial factors may influence neurocognitive functioning, while higher resilience may be associated with more adaptive responses to stress and adversity [31, 32]. The findings provide insight into how digital behavioral patterns may be associated with cognitive and psychological functioning. Although these observations may contribute to understanding behavioral factors related to cognitive vulnerability, the present study does not directly evaluate neurodegeneration, biological markers, neuroimaging changes, or longitudinal cognitive decline. Therefore, the findings should not be interpreted as evidence of direct neuroprotective effects but rather as evidence supporting further investigation of behavioral factors associated with cognitive health.

Within this context, the DNS framework should also be interpreted cautiously. The DNS developed in this study represents an exploratory composite behavioral index, and it has not yet undergone formal

psychometric validation. Although the present study demonstrated associations between DNS categories, cognitive performance, and psychological resilience, it did not assess predictive discrimination, calibration, external validation, or reproducibility across independent populations. Therefore, whether the DNS could have any future utility for screening or risk assessment remains unknown and would require rigorous psychometric evaluation, longitudinal validation, and external validation before any clinical application could be considered.

Limitations

This study had several limitations. First, the cross-sectional, single-center design limited the ability to establish causal relationships between digital behavioral patterns, psychological resilience, and cognitive performance. Although mediation analysis suggested potential indirect associations, the temporal sequence of these relationships cannot be confirmed. Second, digital behavior measures were based on self-report, which may have introduced recall and reporting bias, and residual confounding from unmeasured factors could not be completely excluded. Third, cognitive function was assessed using screening-based measures rather than comprehensive neuropsychological testing, which limited detailed interpretation across specific cognitive domains. Moreover, the DNS represents an exploratory composite behavioral index developed for this study and has not undergone formal psychometric validation. Therefore, its component weighting, classification thresholds, reproducibility, and any potential predictive utility require rigorous evaluation in longitudinal studies and independent populations before clinical or prognostic applications can be considered.

Future research

Future research should focus on validating and refining the DNS framework through longitudinal, multicenter studies. Future investigations should incorporate probability-based sampling strategies, culturally diverse populations, and objective digital behavior measurements obtained through wearable devices or passive digital monitoring approaches. No clinical application should be inferred from the present findings until the construct has undergone appropriate psychometric assessment, longitudinal evaluation, and external validation in independent populations.

Conclusion

This study found that digital behavioral patterns, represented through the exploratory DNS framework, are associated with cognitive function and psychological resilience. The findings suggest that integrating multiple digital lifestyle domains, including screen exposure, sleep patterns, physical activity, and digital engagement behaviors, may provide a useful approach for investigating behavioral factors related to cognitive and psychological outcomes. However, the DNS developed in this study represents a study-specific composite behavioral construct and should not be interpreted as a validated digital biomarker or clinical risk classification tool. Furthermore, given the cross-sectional design, the observed associations and mediation findings should be interpreted cautiously and do not establish causal pathways or direct neuroprotective effects. Future longitudinal, psychometric, and external validation studies are required to determine the reproducibility and generalizability of the DNS framework and to establish whether it has any meaningful predictive utility. Until such evidence is available, the DNS should be regarded as an exploratory research construct, and no clinical or prognostic application should be inferred.

Abbreviations

CD-RISC: Connor-Davidson Resilience Scale

DNS: digital neurobehavioral signature

MoCA: Montreal Cognitive Assessment

OPD: outpatient department

PHQ-9: Patient Health Questionnaire-9

STROBE: Strengthening the Reporting of Observational Studies in Epidemiology

VIF: variance inflation factor

Declarations

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Author contributions

MH: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Writing—original draft, Writing—review & editing. SF: Data curation. Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Writing—original draft, Writing—review & editing. KS: Conceptualization, Data curation, Investigation, Writing—original draft, Writing—review & editing. MAR: Data curation, Investigation, Validation, Supervision, Writing—review & editing. All authors read and approved the submitted version.

Conflicts of interest

The authors declare that they have no conflicts of interest.

Ethical approval

Study was approved by the Ethics Review Committee of Center for Integrated Health Research and Innovation (CIHRI) (Reference No: MS/ERC/029/2025; Date: 01 March 2025) and conducted in accordance with the ethical principles of the Declaration of Helsinki.

Consent to participate

Informed consent to participate in the study was obtained from all participants prior to enrollment.

Consent to publication

Informed consent for the publication of anonymized data was obtained from all participants.

Availability of data and materials

Datasets generated and analyzed during the current study are not publicly available due to institutional data protection policies but are available from the corresponding author upon reasonable request.

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Publisher's note

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