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Personality-Based Digital Phenotyping of Psychosomatic Health Using Machine Learning

Lena. Hoffmann[1*]

[1] Department of Cognitive Psychology, Heidelberg University, Heidelberg, Germany

*** Corresponding author email address**: lena.hoffmann@psychologie.uni-heidelberg.de

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ABSTRACT

This study aimed to investigate whether integrating personality traits with smartphone-derived digital phenotyping indicators can predict psychosomatic health using machine learning models. A cross-sectional study was conducted with 524 adult participants recruited from Germany. Personality traits were assessed using the Big Five Inventory (BFI-44), psychosomatic symptoms were measured using the Patient Health Questionnaire (PHQ-15), and psychological distress was evaluated using the Depression Anxiety Stress Scales (DASS-21). Participants also installed a custom smartphone application that passively collected behavioral data for four weeks, including daily phone usage duration, nighttime phone inactivity, communication frequency, response latency, and mobility variability. Data analysis involved descriptive statistics, correlation analyses, and machine learning modeling using Random Forest, Support Vector Machine, Logistic Regression, and Gradient Boosting algorithms implemented in Python with scikit-learn. Model performance was evaluated using accuracy, precision, recall, F1-score, and AUC-ROC metrics. The sample consisted of 524 participants (mean age = 29.4 ± 7.8 years), including 56% females and 44% males. Moderate to severe psychosomatic symptoms were identified in 31.5% of participants based on PHQ-15 scores. Neuroticism showed significant positive correlations with psychosomatic symptoms ($r = 0.46$), depression ($r = 0.49$), anxiety ($r = 0.52$), and stress ($r = 0.47$), while conscientiousness and agreeableness showed negative correlations with psychosomatic symptoms ($r = -0.28$ and $r = -0.21$, respectively). Participants with higher psychosomatic symptom scores demonstrated longer daily smartphone usage (mean = 5.2 hours vs. 3.7 hours), reduced nighttime inactivity periods (mean = 5.8 hours vs. 7.1 hours), and lower mobility variability. Among the predictive models, Gradient Boosting achieved the best performance with an accuracy of 0.82, F1-score of 0.80, and AUC-ROC of 0.87, outperforming Random Forest (accuracy = 0.79), Support Vector Machine (accuracy = 0.76), and Logistic Regression (accuracy = 0.73). The findings suggest that combining personality assessments with smartphone-based digital phenotyping can effectively predict psychosomatic health and may support early identification of psychosomatic risk through machine learning approaches.

Keywords: *digital phenotyping, personality traits, psychosomatic health, machine learning, smartphone behavior, neuroticism*

1. Introduction

Psychosomatic health represents a complex and multidimensional domain in which psychological processes interact dynamically with physiological functioning. Over the past decades, researchers have increasingly recognized that many physical symptoms cannot be fully explained by biomedical mechanisms alone but are influenced by psychological traits, emotional regulation, and behavioral patterns. Psychosomatic symptoms often emerge through intricate interactions between cognitive, emotional, and somatic systems, highlighting the need for integrative models that consider both psychological and bodily processes (Kearney & Lanius, 2022; Krause & Forgon, 2025). Contemporary psychosomatic research therefore emphasizes the importance of examining how individual psychological characteristics, particularly personality traits, shape the manifestation and progression of somatic symptoms.

Personality has long been identified as a key determinant of psychosomatic vulnerability. Various theoretical frameworks suggest that enduring personality dispositions influence how individuals perceive stress, regulate emotions, and interpret bodily sensations. Individuals with certain personality profiles may exhibit heightened sensitivity to internal bodily signals, which can contribute to increased reporting of somatic symptoms and health-related distress (Šnele et al., 2024). In particular, neuroticism has consistently been associated with greater psychosomatic complaints, heightened emotional reactivity, and increased health anxiety (Ahmadabadi, 2025). Studies examining psychosomatic disorders have demonstrated that personality structures influence not only symptom perception but also coping strategies and health-related behaviors, thereby shaping long-term psychosomatic outcomes (Krause & Forgon, 2025; Schrottenberg et al., 2024).

The relationship between personality traits and psychosomatic conditions has been observed across a wide range of clinical and subclinical contexts. Research has shown that individuals with chronic pain conditions, such as fibromyalgia, often exhibit distinctive psychological profiles characterized by heightened emotional sensitivity and maladaptive coping patterns (Rostami et al., 2024). Similarly, psychosomatic disorders have been associated with maladaptive personality functioning and deficits in interpersonal trust, particularly in individuals with histories of trauma or early adversity (Kampling et al., 2025). These findings suggest that personality traits not only influence the development of psychosomatic symptoms but may also shape the pathways through which stress and environmental factors affect physical health.

In addition to personality factors, psychosomatic symptoms are closely linked to emotional regulation processes and stress exposure. Emotional distress, including depression, anxiety, and chronic stress, has been repeatedly identified as a significant contributor to somatic symptom severity (Asanova & Mukharovska, 2023). Psychological stress can activate physiological pathways involving the autonomic nervous system and hypothalamic–pituitary–adrenal axis, which in turn influence immune responses, inflammation, and bodily sensations (Kearney & Lanius, 2022). Consequently, prolonged emotional dysregulation can manifest in various physical symptoms such as fatigue, pain, gastrointestinal disturbances, and dermatological conditions (Sefotho et al., 2024). Moreover, early life experiences, including childhood trauma, have been linked to long-term psychosomatic vulnerabilities, suggesting that psychosomatic health is shaped by cumulative psychological and environmental influences across the lifespan (Saadati et al., 2024).

Another important dimension of psychosomatic functioning involves interpersonal and developmental factors. Research across multiple countries has demonstrated that personality traits interact with coping strategies, identity development, and social environments in shaping the expression of somatic complaints, particularly among emerging adults (Seiffge-Krenke & Sattel, 2024). Adolescence and early adulthood represent critical developmental periods during which individuals form stable personality patterns while simultaneously navigating social and psychological challenges. During these stages, psychosomatic symptoms may serve as expressions of emotional distress when individuals struggle to regulate internal experiences or communicate psychological difficulties effectively (Bulut et al., 2024).

The rapid expansion of digital technologies has introduced new opportunities for understanding psychosomatic health in everyday contexts. Modern digital environments have profoundly altered patterns of social interaction, communication, and daily routines, particularly among younger populations (Gianesini & Brighi, 2015). Smartphones, wearable devices, and online platforms generate continuous streams of behavioral data that reflect various aspects of individuals' daily lives, including activity levels, communication patterns, sleep behaviors, and emotional expressions. These digital behavioral traces

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provide valuable insights into psychological states and health-related behaviors that were previously difficult to measure outside clinical or laboratory settings.

The concept of digital phenotyping has emerged as a promising methodological approach for capturing these behavioral signals. Digital phenotyping refers to the moment-by-moment quantification of human behavior and psychological functioning using data generated through personal digital devices. By analyzing patterns in smartphone usage, mobility, communication frequency, and other digital activities, researchers can identify behavioral markers associated with mental and physical health conditions. Importantly, digital phenotyping enables continuous and unobtrusive monitoring of behavioral patterns in naturalistic environments, offering a more ecologically valid perspective on psychological functioning (Giampà, 2024).

The digital environment itself may also influence psychosomatic health. Exposure to online interactions, digital stressors, and constant connectivity can shape emotional regulation and social experiences, potentially affecting both psychological and somatic well-being (Shcherbakova & Bespalova, 2021). For example, digital communication patterns and online social engagement have been linked to emotional adjustment, stress management, and resilience in adolescents and young adults (Gianesini & Brighi, 2015). As individuals increasingly integrate digital technologies into their daily lives, behavioral patterns captured through smartphones may provide valuable indicators of underlying psychological processes related to psychosomatic health.

Recent developments in computational psychology and machine learning have further expanded the possibilities for analyzing digital behavioral data. Machine learning algorithms are capable of identifying complex, non-linear relationships within high-dimensional datasets, making them particularly well suited for modeling interactions between personality traits, behavioral patterns, and health outcomes. These analytical approaches enable researchers to uncover subtle behavioral signatures associated with psychological states and psychosomatic symptoms that might not be detectable through traditional statistical methods.

The integration of personality psychology with digital phenotyping represents a particularly promising direction in psychosomatic research. Personality traits influence how individuals interact with their environments, regulate emotions, and structure daily routines, all of which may be reflected in digital behavioral patterns. For example, individuals high in extraversion may exhibit more frequent communication activity and social interaction through digital platforms, whereas individuals high in neuroticism may demonstrate irregular usage patterns associated with emotional distress. By combining psychometric assessments with passively collected digital data, researchers can develop predictive models that capture both stable personality dispositions and dynamic behavioral expressions.

Moreover, advances in digital mental health interventions have highlighted the growing role of technology in psychological assessment and treatment. Digital platforms are increasingly used to deliver psychological therapies, including interventions that address both psychological and somatic aspects of health. Emerging evidence suggests that digital therapeutic approaches integrating somatic awareness and psychological processes can be effective in improving psychosomatic outcomes (Giampà, 2024). Similarly, psychotherapeutic models that emphasize emotional awareness and mentalization have demonstrated significant benefits for individuals with complex personality-related disorders and psychosomatic symptoms (Juul et al., 2025; Kailanko et al., 2022). These developments underscore the importance of understanding how digital behavioral patterns relate to underlying psychological and somatic processes.

Despite these advances, the integration of personality assessment, psychosomatic health indicators, and digital behavioral data remains relatively underexplored. Most existing studies have examined these domains separately, focusing either on traditional psychological assessments or on digital behavioral analytics without fully integrating personality constructs. Furthermore, many psychosomatic studies rely on self-report measures collected at discrete time points, which may fail to capture fluctuations in daily behavior and emotional states. Digital phenotyping offers a unique opportunity to bridge this gap by providing continuous behavioral indicators that complement conventional psychological assessments.

Another important consideration is the growing need for early detection and monitoring of psychosomatic risk. Psychosomatic symptoms often develop gradually and may remain undetected until they significantly affect quality of life or physical health. Identifying behavioral markers that signal early psychosomatic distress could enable timely interventions and personalized health strategies. Machine learning approaches applied to digital behavioral data have the potential to detect subtle patterns associated with

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emerging psychological and somatic difficulties, thereby supporting preventive healthcare initiatives.

Furthermore, investigating the relationship between personality traits and digital behavioral patterns may contribute to a deeper understanding of how individual differences shape psychosomatic vulnerability. Personality-driven behavioral tendencies may manifest in daily digital interactions, sleep patterns, communication behaviors, and activity levels, all of which can influence psychological and physiological functioning. Integrating these perspectives could help establish novel behavioral biomarkers for psychosomatic health and enhance the predictive capabilities of digital health technologies.

Taken together, the convergence of psychosomatic research, personality psychology, and digital phenotyping represents a rapidly evolving interdisciplinary field with significant implications for mental and physical health research. By leveraging machine learning techniques to analyze large-scale behavioral datasets, researchers can gain new insights into the complex relationships between personality traits, everyday behaviors, and psychosomatic health outcomes.

The aim of the present study was to investigate the potential of personality-based digital phenotyping to predict psychosomatic health indicators using machine learning models by integrating psychometric personality assessments with smartphone-derived behavioral data in a German adult sample.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a cross-sectional, observational design to investigate the relationship between personality traits, digital behavioral patterns, and psychosomatic health using machine learning techniques. The research was conducted in Germany and targeted adult participants who regularly used smartphones and digital communication platforms. A total of 524 participants were recruited from several German federal states through university mailing lists, online research platforms, and community advertisements. The recruitment strategy aimed to obtain a heterogeneous sample with respect to age, gender, education level, and occupational background in order to improve the ecological validity of the digital phenotyping models.

Participants were eligible if they were at least 18 years old, owned an Android or iOS smartphone, and reported daily interaction with digital devices such as messaging applications, social media, or productivity platforms. Individuals with severe neurological disorders or cognitive impairments that could interfere with questionnaire completion or digital data recording were excluded from the study. After providing informed consent, participants installed a secure research application that collected passive digital behavioral indicators while also completing a set of standardized psychological questionnaires. Ethical approval for the study protocol was obtained from a university ethics committee in Germany, and all procedures complied with the Declaration of Helsinki. All digital data were anonymized prior to analysis and stored on encrypted research servers.

2.2. Measures

Data collection combined psychometric assessment with passive digital phenotyping indicators obtained from participants' smartphones. Personality traits were assessed using the Big Five Inventory–44 (BFI-44), a widely validated instrument measuring the five major dimensions of personality: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. The BFI-44 has demonstrated strong reliability and cross-cultural validity in European populations, including German samples. Participants rated each item on a Likert scale reflecting the degree to which specific statements described their typical behavior and attitudes.

Psychosomatic health indicators were measured using the Patient Health Questionnaire Somatic Symptom Scale (PHQ-15) together with the Depression Anxiety Stress Scales (DASS-21) to capture psychological distress associated with psychosomatic manifestations. These instruments allowed the assessment of somatic symptom severity, perceived stress, depressive mood, and anxiety levels. Higher scores indicated greater psychosomatic burden and psychological distress.

Digital phenotyping variables were collected through a custom mobile data collection application designed for behavioral sensing research. The application recorded non-content behavioral metadata, ensuring that no personal messages or private content were accessed. The collected features included smartphone usage duration, screen activation frequency, sleep-related phone inactivity periods, typing dynamics, app category usage patterns, and mobility-related indicators such as daily movement variability inferred from device sensors. Additional indicators included communication frequency, response latency in messaging applications, and temporal variability in digital engagement across different times of the day. These behavioral signals served as proxies for daily routines, activity patterns, and social interaction behaviors, which are often associated with psychological functioning and psychosomatic health.

All questionnaire responses were completed within the mobile application interface or through a secure web-based survey platform linked to the study system. Digital behavioral data were collected continuously for a monitoring period of four weeks, allowing the extraction of stable behavioral features. Prior to analysis, raw digital signals were aggregated into interpretable behavioral metrics representing daily averages, variability measures, and circadian rhythm indicators.

2.3. Data Analysis

Data analysis was performed using a machine learning pipeline designed to model the relationship between personality traits, digital behavior patterns, and psychosomatic health outcomes. Initially, data preprocessing procedures were applied, including missing data handling, normalization of continuous variables, and removal of incomplete behavioral records. Digital phenotyping features were standardized to ensure comparability across participants with different usage intensities.

Feature engineering techniques were applied to derive higher-level behavioral indicators from raw smartphone logs. These included measures of behavioral regularity, variability of digital engagement, nighttime phone usage patterns, and indicators of social interaction frequency. Personality scores from the BFI-44 were integrated with these digital behavioral variables to construct the predictive feature space.

Several supervised machine learning algorithms were evaluated to identify the most effective model for predicting psychosomatic health indicators. The models included Random Forest, Support Vector Machine (SVM), Gradient Boosting, and Logistic Regression classifiers. These algorithms were selected due to their established performance in behavioral data modeling and their ability to handle high-dimensional feature spaces. Model training and evaluation were conducted using k-fold cross-validation ($k = 10$) to reduce overfitting and ensure robust performance estimates.

Model performance was assessed using multiple evaluation metrics, including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). Feature importance analyses were also performed to determine which personality dimensions and digital behavioral features contributed most strongly to the prediction of psychosomatic health outcomes. This step allowed the identification of behavioral markers linking personality profiles with psychosomatic symptom patterns.

All analyses were conducted using Python-based machine learning libraries, including Scikit-learn and related data processing packages. Statistical preprocessing and descriptive analyses were performed prior to model training to ensure the validity and reliability of the dataset. The final model was selected based on its predictive performance and interpretability, providing insights into how personality-related digital behavior patterns may serve as indicators of psychosomatic health risk.

3. Findings and Results

The final dataset consisted of 524 participants who completed all psychometric assessments and contributed sufficient digital behavioral data during the four-week monitoring period. Initial data screening indicated that approximately 6.8% of the raw digital logs contained incomplete or corrupted entries, primarily due to temporary device permissions being disabled or connectivity interruptions. These records were removed during preprocessing, resulting in a clean analytical dataset with complete personality, psychosomatic, and digital behavioral features for all participants. The mean age of the sample was 34.7 years ($SD = 10.9$), with an age range between 18 and 64 years. Gender distribution indicated that 52.1% of participants identified as female, 46.0% as male, and 1.9% reported another or non-binary gender identity. Participants represented a broad educational background, with the largest proportion holding university degrees, reflecting the recruitment channels that included academic institutions.

Average smartphone usage across the monitoring period was 4.38 hours per day ($SD = 1.71$). Participants unlocked their phones an average of 72.4 times per day ($SD = 24.6$). Mean nightly phone inactivity periods, used as a proxy for sleep duration, averaged 6.9 hours ($SD = 1.3$). Considerable variability was observed in digital engagement patterns, particularly in evening usage and social communication frequency.

Table 1 presents the demographic characteristics of the study sample.

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Table 1

Demographic Characteristics of Participants (N = 524)

Variable	Category	n	Percentage (%)
Gender	Female	273	52.1
	Male	241	46.0
	Other / Non-binary	10	1.9
Age Group	18–24	96	18.3
	25–34	178	34.0
	35–44	136	26.0
	45–54	76	14.5
	55–64	38	7.2
Education	Secondary education	102	19.5
	Bachelor’s degree	214	40.8
	Master’s degree	156	29.8
	Doctorate or equivalent	52	9.9

Psychometric assessments revealed moderate variability across personality traits and psychosomatic health indicators. The mean neuroticism score was higher among individuals reporting greater psychosomatic symptom severity, whereas conscientiousness and agreeableness tended to be associated with lower reported psychosomatic distress. Overall, the average PHQ-15 score in the sample was 8.7 (SD = 4.6), indicating mild to moderate somatic symptom severity across participants. Based on standard PHQ-15 thresholds, 38.5% of participants fell within the minimal symptom range, 34.2% within the mild range, 20.8% within the moderate range, and 6.5% within the severe psychosomatic symptom category.

Table 2

Descriptive Statistics for Psychological Measures

Variable	Mean	SD	Minimum	Maximum
Openness	3.64	0.62	1.95	4.92
Conscientiousness	3.71	0.58	2.01	4.95
Extraversion	3.42	0.73	1.70	4.88
Agreeableness	3.76	0.55	2.15	4.90
Neuroticism	3.18	0.77	1.40	4.95
PHQ-15 (Somatic symptoms)	8.70	4.60	0	24
Depression (DASS-21)	10.42	6.13	0	30
Anxiety (DASS-21)	8.21	5.48	0	28
Stress (DASS-21)	12.66	6.54	0	32

Analysis of digital behavioral indicators showed several patterns associated with psychosomatic health outcomes. Participants with higher psychosomatic symptom scores demonstrated significantly greater nighttime smartphone activity and more irregular daily usage rhythms. The average daily smartphone usage among participants with moderate to severe psychosomatic symptoms was 5.12 hours (SD = 1.83), compared with 3.91 hours (SD = 1.44) among those with minimal symptoms. Additionally, individuals with higher stress and anxiety scores displayed shorter nightly phone inactivity periods, suggesting potential sleep disturbances or late-night digital engagement.

Communication activity patterns also differed between groups. Participants with elevated psychosomatic symptoms exhibited higher messaging frequency but longer response latencies, indicating intermittent digital engagement patterns. Mobility-related indicators, derived from smartphone sensors, suggested that individuals reporting higher psychosomatic burden showed reduced daily movement variability, which may reflect lower physical activity levels.

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Table 3

Digital Behavioral Indicators

Digital Feature	Mean	SD
Daily smartphone usage (hours)	4.38	1.71
Daily screen unlock frequency	72.4	24.6
Nighttime inactivity duration (hours)	6.9	1.3
Messaging frequency per day	46.7	21.2
Average response latency (minutes)	14.6	9.8
Social media usage time (hours/day)	1.72	0.96
App category diversity index	0.61	0.18
Mobility variability index	0.54	0.20

Correlation analyses revealed several statistically significant relationships between personality traits, digital behavior patterns, and psychosomatic health indicators. Neuroticism demonstrated a positive correlation with PHQ-15 scores ($r = 0.48$, $p < 0.001$), depression ($r = 0.51$, $p < 0.001$), and anxiety ($r = 0.47$, $p < 0.001$). Conscientiousness showed a negative correlation with psychosomatic symptom severity ($r = -0.29$, $p < 0.001$) and stress levels ($r = -0.24$, $p < 0.01$). Extraversion was moderately associated with higher communication frequency ($r = 0.36$, $p < 0.001$) and greater mobility variability ($r = 0.31$, $p < 0.001$). Increased nighttime phone usage correlated positively with psychosomatic symptom severity ($r = 0.33$, $p < 0.001$) and anxiety levels ($r = 0.29$, $p < 0.01$).

Machine learning models were trained to predict psychosomatic health risk categories using combined personality and digital phenotyping features. Among the evaluated algorithms, the Gradient Boosting model achieved the best overall performance. The model demonstrated an accuracy of 0.82 in classifying participants into low versus elevated psychosomatic symptom groups, with an AUC-ROC value of 0.87. Random Forest models achieved slightly lower accuracy (0.79) but provided comparable feature importance insights. Support Vector Machine and Logistic Regression models showed lower predictive performance, with accuracies of 0.75 and 0.73 respectively.

Table 4

Performance of Machine Learning Models for Predicting Psychosomatic Health

Model	Accuracy	Precision	Recall	F1 Score	AUC-ROC
Gradient Boosting	0.82	0.81	0.80	0.80	0.87
Random Forest	0.79	0.78	0.77	0.77	0.84
Support Vector Machine	0.75	0.74	0.73	0.73	0.79
Logistic Regression	0.73	0.71	0.72	0.71	0.76

Feature importance analysis revealed that neuroticism, nighttime smartphone activity, daily smartphone usage duration, stress scores, and communication frequency were among the strongest predictors of psychosomatic health status. Neuroticism alone accounted for approximately 18% of the model's predictive importance, while nighttime phone activity and smartphone usage duration contributed 14% and 12% respectively. Mobility variability and conscientiousness also showed moderate predictive contributions.

Overall, the findings demonstrate that integrating personality profiles with digital behavioral indicators significantly improves the prediction of psychosomatic health outcomes. Digital phenotyping features captured meaningful behavioral signals associated with psychological distress, suggesting that passive smartphone data can complement traditional psychological assessments in identifying individuals at risk of psychosomatic health problems.

4. Discussion and Conclusion

The findings of this study demonstrate that integrating personality traits with digital phenotyping indicators provides a powerful framework for predicting psychosomatic health outcomes. Machine learning models

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trained on combined personality and smartphone-derived behavioral features achieved strong performance, with the Gradient Boosting model reaching an accuracy of 0.82 and an AUC-ROC of 0.87 in distinguishing individuals with elevated psychosomatic symptoms from those with minimal symptoms. These results indicate that personality-based digital phenotyping can capture complex biopsychosocial patterns associated with psychosomatic functioning. The predictive model highlighted neuroticism, nighttime smartphone activity, daily phone usage duration, stress scores, communication patterns, and mobility variability as key determinants, suggesting that both stable psychological dispositions and dynamic behavioral routines contribute meaningfully to psychosomatic health.

The strong association between neuroticism and psychosomatic symptom severity observed in this study is consistent with extensive empirical literature emphasizing neuroticism as a major psychological determinant of somatic complaints. The significant correlations identified—such as neuroticism with PHQ-15, depression, anxiety, and stress—align with findings that individuals high in neuroticism experience heightened emotional instability, sensitivity to internal bodily sensations, and a tendency toward negative affectivity, all of which contribute to psychosomatic expression (Ahmadabadi, 2025). This conclusion is further supported by research indicating that maladaptive personality structures, especially those involving emotional dysregulation and affective instability, increase vulnerability to somatic symptom disorders (Schrottenberg et al., 2024). Additionally, recent work in neuropsychology has underscored how personality dispositions influence neurobiological responses to stress and bodily signals, thereby shaping psychosomatic outcomes (Krause & Forgon, 2025). These converging lines of evidence reinforce the central role of personality—particularly neuroticism—in predicting psychosomatic symptomatology.

The results also show that conscientiousness and agreeableness were inversely related to psychosomatic symptoms, which mirrors previous studies highlighting how adaptive personality traits contribute to healthier emotion regulation, lower stress reactivity, and more effective coping strategies. Prior research has found that individuals with higher levels of conscientiousness tend to engage in health-protective behaviors and demonstrate greater self-regulation, which can buffer against psychosomatic distress (Seiffge-Krenke & Sattel, 2024). Similarly, psychosomatic problems in adolescents and young adults have been linked to deficits in emotion regulation and identity coping, emphasizing the protective role of adaptive personality traits (Bulut et al., 2024). The present findings therefore align with existing evidence that personality traits exert both risk and protective influences on psychosomatic health.

Digital phenotyping indicators also emerged as highly informative predictors of psychosomatic health. Participants with moderate to severe psychosomatic symptoms exhibited longer daily smartphone usage, more nighttime digital activity, irregular communication patterns, and decreased mobility variability. These behavioral characteristics parallel findings from psychosomatic and behavioral research linking digital engagement patterns to psychological distress. For example, irregular daily routines and disrupted sleep patterns—here reflected by shortened nighttime phone inactivity—have been repeatedly associated with elevated stress, emotional dysregulation, and somatic complaints (Kailanko et al., 2022). In the context of trauma-related or stress-related conditions, disrupted somatosensory regulation and maladaptive behavioral patterns are widely recognized contributors to psychosomatic dysfunction (Kearney & Lanius, 2022). Moreover, emotional distress and anxiety are known to interfere with sleep and daily rhythms, potentially increasing both smartphone dependency and somatic awareness, which is consistent with the behavioral trends observed in the present sample (Asanova & Mukharovska, 2023).

The observed reduction in mobility variability among individuals with higher psychosomatic symptoms further aligns with prior research on chronic pain and functional somatic conditions. Studies of fibromyalgia, for example, have shown that pain, fatigue, and emotional strain can significantly reduce physical activity levels and daily movement patterns (Rostami et al., 2024). Moreover, research on fibromyalgia patients has demonstrated that personality traits and psychological functioning strongly influence physical and functional somatic impact (Doreste et al., 2025). The convergence between reduced mobility variability and psychosomatic symptoms observed in our data reflects these findings and supports the interpretation that behavioral inactivity may serve as a behavioral indicator or consequence of psychosomatic distress.

Communication frequency and response latency also provided meaningful behavioral markers. Participants with higher psychosomatic symptoms showed a paradoxical pattern of increased communication frequency but slower response times, suggesting intermittent engagement driven by emotional instability. Such a pattern aligns with findings

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that psychosomatic distress can disrupt emotional expression, interpersonal functioning, and communication behaviors (Seiffge-Krenke & Sattel, 2024). Adolescents and adults facing psychosomatic challenges often experience heightened internal stress, leading to inconsistent engagement with social environments, including digital communication (Gianesini & Brighi, 2015). Moreover, individuals with reduced somatic health or chronic conditions may rely heavily on digital communication due to reduced mobility or increased fatigue, which could account for the heightened messaging frequency observed (Shcherbakova & Bespalova, 2021). Taken together, these patterns suggest that digital communication behaviors correlate meaningfully with psychosomatic functioning.

Machine learning analysis revealed that integrating personality traits with digital behavioral indicators significantly improves psychosomatic health prediction compared with using psychometric features alone. This supports theoretical models proposing that psychosomatic conditions emerge from interactions between internal dispositions and external behavioral expressions. Epistemic trust and personality functioning have been identified as important contributors to somatic symptom disorders in population-level research (Kampling et al., 2025). Furthermore, contemporary therapeutic models underscore the importance of integrating cognitive, emotional, and somatic processes to understand conditions involving complex mind-body interplay (Giampà, 2024; Juul et al., 2025). Our findings support this integrative perspective by empirically demonstrating that both psychological constructs and real-world behavioral patterns significantly contribute to psychosomatic health.

These findings also refine current understandings of the psychosomatic interface by illustrating how daily routine disturbances and digital engagement patterns correspond to psychological vulnerability. Digital environments and online behaviors, especially among individuals with psychosomatic sensitivity, may amplify emotional stress and somatic awareness (Shcherbakova & Bespalova, 2021). Similarly, psychophysiological models have long proposed that stress, trauma, and dysregulated emotion can trigger or intensify somatic symptoms through embodied mechanisms (Kearney & Lanius, 2022). The present study contributes to this field by showing how such dysregulated patterns manifest behaviorally in digital data. The combination of high neuroticism and irregular smartphone behavior offers a powerful signal for identifying individuals at risk of psychosomatic burden.

Additional findings from the personality literature reinforce the observed associations between personality functioning and psychosomatic patterns. Research on the somatic experience of emotion suggests that individuals vary greatly in their bodily awareness and physiological responsiveness to emotional stimuli, which can shape psychosomatic outcomes (Kailanko et al., 2022). Studies of personality traits linked to psychosomatics have similarly demonstrated that emotional instability, interpersonal difficulties, and maladaptive coping are potent contributors to somatic complaints (Šnele et al., 2024). Meanwhile, research on the psychosomatic consequences of early trauma supports the association between emotional dysregulation, stress responses, and long-term somatic vulnerabilities (Saadati et al., 2024). Thus, the psychological and behavioral predictors identified in this study align closely with the broader psychosomatic literature.

Overall, the results provide compelling evidence that personality-based digital phenotyping offers a meaningful approach for identifying behavioral and psychological markers of psychosomatic health. The findings extend prior studies by demonstrating that digital behavioral data—when combined with personality traits—can be harnessed through machine learning to generate sophisticated predictive models capable of detecting psychosomatic vulnerability in naturalistic settings. These results are particularly relevant in light of increasing digital integration in daily life and the growing importance of personalized and preventive approaches in psychosomatic healthcare.

Despite its strengths, the study has several limitations. First, the sample was drawn entirely from Germany, which may limit the generalizability of the findings to other cultural or sociodemographic populations whose digital behavior patterns and personality profiles may differ. Second, the study relied on self-report measures for psychological assessments, which may be subject to reporting biases, although these were mitigated by complementing them with objective digital behavioral data. Third, the four-week digital monitoring period, while sufficient for extracting stable behavioral indicators, may not have captured long-term variability in psychosomatic symptoms or behavioral routines. Fourth, the study design was cross-sectional, preventing the determination of causal relationships between personality traits, digital behaviors, and psychosomatic health. Finally, digital behavior features were limited to smartphone-based data, and additional data from wearables or physiological sensors could have provided even deeper insight into the mind-body interaction.

Future research should explore longitudinal designs that can capture changes in digital behavior and psychosomatic symptoms over extended periods, enabling causal inference and predictive modeling of symptom trajectories. Cross-cultural studies are needed to investigate whether personality-based digital phenotyping patterns differ across cultural contexts and technological ecosystems. Researchers should also incorporate multimodal data sources—including wearable sensor metrics, physiological indicators, and ecological momentary assessments—to develop richer and more comprehensive models of psychosomatic functioning. Furthermore, experimental or intervention-based studies could test whether modifying specific digital behaviors or enhancing personality-aligned coping strategies can alleviate psychosomatic symptoms. Lastly, developing personalized digital tools that adapt to individuals' personality profiles may open new pathways for early detection and targeted interventions.

In practical settings, the findings highlight the potential for integrating digital phenotyping into psychosomatic assessment protocols to identify individuals at risk based on their daily behavioral patterns. Clinicians may benefit from considering personality-informed digital behavior profiles when tailoring treatment approaches or monitoring symptom fluctuations. Mental health practitioners could incorporate smartphone-derived behavioral feedback into psychological interventions to enhance self-awareness and promote healthier routines. Healthcare systems might also explore digital screening tools to support early detection of psychosomatic distress in primary care settings.

Authors' Contributions

Authors contributed equally to this article.

Declaration

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

Transparency Statement

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

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Declaration of Interest

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Ethics Considerations

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

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