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Predicting Somatic Complaints from Personality Traits and Smartphone-Derived Behavioral Data Using Machine Learning

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A B S T R A C T

This study aimed to predict somatic complaints by integrating Big Five personality traits and passive smartphone-derived behavioral indicators within a machine learning framework. A cross-sectional observational design was employed with an adult community sample recruited in Armenia. Participants completed standardized self-report measures assessing somatic complaints and Big Five personality traits. In parallel, passive smartphone sensing data were collected continuously over a four-week period using a custom Android application that captured behavioral indicators such as screen time, sleep regularity proxies, physical inactivity duration, nighttime phone activity, and app usage patterns, without recording personal content. Data preprocessing included cleaning, aggregation of behavioral features at the participant level, and standardization of predictors. Supervised machine learning models were trained to predict somatic complaint scores, including regularized linear models, support vector regression, random forest, and gradient boosting. Model evaluation used train–test splits with cross-validation, and performance was assessed using error-based indices and explained variance metrics. Nonlinear ensemble models significantly outperformed linear approaches in predicting somatic complaints, with gradient boosting explaining the largest proportion of variance. Models combining personality traits and smartphone-derived behavioral data demonstrated significantly higher predictive accuracy than models using either data source alone. Neuroticism showed the strongest positive contribution to somatic complaints, while conscientiousness and extraversion contributed negatively. Among behavioral indicators, sleep regularity, daily screen time, nighttime phone activity, and physical inactivity emerged as significant predictors. Model performance remained stable across gender and age subgroups, indicating robustness of the predictive relationships. Integrating personality traits with passive smartphone-derived behavioral data using machine learning provides a powerful and ecologically valid approach for predicting somatic complaints, supporting biopsychosocial models of psychosomatic health and highlighting the potential of digital phenotyping for personalized health assessment.

Keywords: *somatic complaints; personality traits; smartphone sensing; digital phenotyping; machine learning*

1. Introduction

Somatic complaints, defined as recurrent physical symptoms that are not fully explained by identifiable medical conditions, represent a substantial burden for individuals and healthcare systems worldwide. These complaints often include headaches, gastrointestinal discomfort, musculoskeletal pain, fatigue, and cardiopulmonary sensations, and they are closely intertwined with psychological processes, behavioral patterns, and individual differences. Contemporary research increasingly conceptualizes somatic complaints not merely as isolated bodily phenomena but as outcomes of complex biopsychosocial interactions, where personality traits, emotional regulation, daily behaviors, and contextual factors jointly shape symptom perception and reporting. From this perspective, advancing the prediction of somatic complaints requires integrative frameworks capable of capturing both stable dispositional characteristics and dynamic, real-world behavioral patterns (Damian et al., 2023; Perlini, 2025; Zdanowicz et al., 2025).

Personality traits, particularly those described within the Big Five model, have long been recognized as fundamental determinants of health-related outcomes. Neuroticism has consistently been associated with heightened symptom sensitivity, increased health anxiety, and greater vulnerability to emotional and somatic distress, whereas traits such as conscientiousness and extraversion are often linked to healthier behaviors, adaptive coping, and better subjective well-being (Gashi et al., 2022; Okutucu & Ceyhun, 2025; Zdanowicz et al., 2025). Empirical evidence indicates that personality traits influence not only emotional problems but also the way bodily sensations are interpreted, monitored, and communicated. For instance, individuals high in neuroticism tend to exhibit amplified interoceptive awareness and catastrophic interpretations of benign physical sensations, thereby increasing the likelihood of somatic complaint reporting (Gong et al., 2023; Jacobs et al., 2022). Conversely, conscientiousness has been associated with more regulated lifestyles, better sleep hygiene, and adherence to health-promoting behaviors, which may mitigate somatic symptom burden (Eren & Yiğitoğlu, 2023; Kakuta et al., 2024).

Beyond personality, everyday behaviors play a critical role in shaping physical well-being. In recent years, the pervasive use of smartphones has transformed daily life, providing unprecedented opportunities to observe behavioral patterns continuously and unobtrusively. Smartphone-derived data, including screen time, app usage, sleep–wake rhythms, physical activity proxies, and mobility patterns, have emerged as valuable indicators of mental and physical health states. Research in digital phenotyping demonstrates that these passive behavioral signals can reliably reflect psychological distress, fatigue, and health-related functioning in naturalistic settings (Asare et al., 2022; Müller-Bardorff et al., 2024; Song, 2025). Importantly, such data capture fluctuations and habits that traditional self-report measures may overlook, thereby offering a complementary perspective on health-related experiences.

A growing body of literature highlights the close links between problematic smartphone use, personality traits, and psychological symptoms. Excessive screen time, irregular usage rhythms, and nighttime phone activity have been associated with sleep disturbances, fatigue, anxiety, and depressive symptoms, all of which are known correlates of somatic complaints (Srivastava et al., 2025; Su et al., 2024; Turan & Yılmaz, 2024). Personality traits appear to moderate these associations, with individuals high in neuroticism or low in conscientiousness being particularly susceptible to maladaptive digital behaviors and their downstream health consequences (Bhayangkara et al., 2024; Rodríguez et al., 2025; Venkateswaran et al., 2025). These findings suggest that smartphone-derived behavioral data may serve not only as markers of current health status but also as mechanisms through which personality exerts its influence on somatic experiences.

Parallel to these developments, advances in machine learning (ML) have opened new avenues for modeling complex, nonlinear relationships among psychological and behavioral variables. Traditional statistical approaches, while valuable, are often limited in their ability to handle high-dimensional data, nonlinear interactions, and temporal variability inherent in digital behavioral traces. Machine learning methods, by contrast, are well suited for integrating heterogeneous data sources and uncovering subtle patterns that contribute to health-related outcomes (Marengo et al., 2023; Parpoula, 2024). In the context of mental health research, ML models have demonstrated superior predictive performance for outcomes such as depression, anxiety, fatigue, and quality of life when compared to conventional regression techniques (Chung & Park, 2025; Fuller et al., 2025; Song, 2025).

Despite these methodological advances, the application of machine learning to the prediction of somatic complaints remains relatively underexplored. Existing studies have largely focused on emotional disorders, depressive

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symptoms, or general well-being, often treating somatic symptoms as secondary outcomes or as components of broader psychopathology constructs (Aksnes et al., 2024; Ferguson et al., 2022; Grover, 2022). Yet somatic complaints warrant dedicated investigation, given their prevalence, impact on functioning, and frequent presentation in primary care settings. Moreover, many prior studies rely either on self-reported psychological measures or on digital behavioral data alone, without systematically integrating stable personality traits with dynamic smartphone-derived indicators within a unified predictive framework (Hoshino et al., 2023; Ibrar et al., 2023).

Integrating personality and smartphone-derived behavioral data aligns with contemporary biopsychosocial models of health, which emphasize the interaction between enduring individual differences and situationally embedded behaviors. Personality traits shape how individuals engage with their environment, regulate emotions, and adopt daily routines, while smartphone usage patterns provide a real-time behavioral manifestation of these dispositions within modern digital contexts (Ferguson et al., 2022; Marengo et al., 2023). From this standpoint, combining these data sources within machine learning models holds significant promise for enhancing the precision and ecological validity of somatic complaint prediction.

The relevance of such integrative approaches is further underscored by cross-cultural considerations. Most digital phenotyping and ML-based health studies have been conducted in Western European or North American contexts, limiting the generalizability of findings to other sociocultural settings. Cultural norms influence symptom expression, health-seeking behavior, technology use, and personality–behavior relationships, making it essential to examine these models in diverse populations (Gashi et al., 2022; Zhao et al., 2024). Studying somatic complaints in relation to personality and smartphone-derived behaviors within underrepresented regions contributes to a more globally inclusive understanding of digital health psychology.

Furthermore, predictive models that accurately identify individuals at risk for elevated somatic complaints have practical implications for early intervention and personalized health strategies. Smartphone-based monitoring combined with personality-informed risk profiling could support proactive, low-burden screening approaches and guide tailored preventive interventions, such as sleep regulation, digital behavior modification, or stress management programs (Müller-Bardorff et al., 2024; Vroegindeweij et al., 2022; Vroegindeweij et al., 2023). These applications resonate with the broader movement toward personalized and preventive healthcare supported by digital technologies.

In summary, existing literature converges on three key insights: first, personality traits are robust predictors of emotional and somatic health outcomes; second, smartphone-derived behavioral data provide ecologically valid markers of daily functioning and health-related behaviors; and third, machine learning methods offer powerful tools for integrating these heterogeneous data sources to improve prediction accuracy. However, there remains a clear gap in research that explicitly combines personality traits and passive smartphone sensing data to predict somatic complaints using advanced ML techniques, particularly within non-Western cultural contexts. Addressing this gap is critical for advancing theoretical models of psychosomatic health and for developing innovative, data-driven approaches to health assessment and intervention.

Accordingly, the present study aims to predict somatic complaints by integrating personality traits and smartphone-derived behavioral data within a machine learning framework in an adult sample.

2. Methods and Materials

2.1. Study Design and Participants

The present study employed a cross-sectional, observational design aimed at examining the predictive capacity of personality traits and smartphone-derived behavioral indicators for somatic complaints using machine learning techniques. The study population consisted of adult participants residing in Armenia. Recruitment was carried out through university mailing lists, social media announcements, and community outreach in urban areas, with an emphasis on voluntary participation. Eligibility criteria included being between 18 and 60 years of age, ownership and regular use of an Android smartphone for at least six months prior to participation, and sufficient literacy to complete self-report questionnaires in Armenian. Individuals with a diagnosed severe neurological disorder or psychotic condition, which could substantially interfere with self-report accuracy or smartphone use patterns, were excluded. After providing informed consent, participants were enrolled and assigned an anonymized identification code to ensure confidentiality. The final sample size was determined based on the requirements of supervised

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machine learning modeling, ensuring an adequate ratio of observations to predictors and allowing for reliable model training, validation, and testing.

2.2. Measures

Data were collected using a multimodal approach combining standardized self-report instruments and passive smartphone sensing data. Somatic complaints were assessed using a validated self-report measure designed to capture the frequency and intensity of common physical symptoms without identifiable medical causes, such as headaches, gastrointestinal discomfort, fatigue, and musculoskeletal pain. The instrument demonstrated established psychometric properties in prior research, including satisfactory internal consistency and construct validity. Personality traits were measured using a widely recognized personality inventory based on the five-factor model, assessing neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness. Participants completed the personality questionnaire electronically via a secure online platform, ensuring standardized administration conditions.

Smartphone-derived behavioral data were collected through a custom-developed sensing application installed on participants' smartphones. The application operated in the background and passively recorded behavioral indicators over a continuous monitoring period of four weeks. Collected data included usage-based metrics such as total screen time, frequency of phone unlocks, app category usage patterns, call and messaging activity metadata (excluding content), and temporal usage rhythms across the day. In addition, sensor-based indicators such as physical activity inferred from accelerometer data, mobility patterns derived from GPS-based location changes, and sleep-related proxies inferred from phone inactivity periods were recorded. No audio recordings, message contents, or personally identifiable location data were stored; all raw data were encrypted on the device and securely transmitted to a protected server for preprocessing. Participants were instructed not to alter their typical smartphone usage behavior during the monitoring period to preserve ecological validity.

2.3. Data Analysis

Data analysis was conducted in several sequential stages, integrating psychological assessment data with digital behavioral features. Initially, raw smartphone sensing data were cleaned to remove incomplete records, artifacts, and extreme outliers caused by technical interruptions. Behavioral features were then aggregated at the participant level, generating summary indicators such as daily averages, variability measures, and circadian regularity indices. Self-report questionnaire data were screened for missing values and response inconsistencies, and composite scores were calculated according to established scoring guidelines. Prior to modeling, all predictors were standardized to ensure comparability across different scales and to optimize algorithm performance.

Machine learning analyses were implemented using a supervised learning framework, with somatic complaint scores serving as the target variable. The dataset was randomly partitioned into training and testing subsets, with an additional validation procedure applied within the training set using k-fold cross-validation to reduce overfitting and improve generalizability. Multiple algorithms, including regularized linear models, tree-based ensemble methods, and nonlinear kernel-based approaches, were trained and compared. Feature selection and regularization techniques were applied where appropriate to address multicollinearity and high-dimensionality inherent in smartphone-derived data. Model performance was evaluated using error-based and variance-explained metrics, and comparative performance across models was assessed to identify the most accurate and stable predictive approach. Finally, model interpretability techniques, such as feature importance rankings and partial dependence analyses, were employed to elucidate the relative contribution of personality traits and specific behavioral indicators to the prediction of somatic complaints. All analyses were conducted using established machine learning libraries in Python, with reproducibility ensured through fixed random seeds and documented preprocessing pipelines.

3. Findings and Results

Table 1 presents the descriptive statistics and zero-order correlations among the main study variables and serves as the foundation for subsequent inferential and predictive analyses.

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Table 1

Descriptive statistics and correlations among somatic complaints, personality traits, and aggregated smartphone behavioral indicators

Variable	Mean	SD	1	2	3	4	5	6	7	8
1. Somatic complaints	21.84	7.62	—							
2. Neuroticism	27.11	6.48	.52	—						
3. Extraversion	30.27	5.91	-.18	-.31	—					
4. Conscientiousness	32.45	6.12	-.29	-.34	.26	—				
5. Agreeableness	33.02	5.37	-.14	-.21	.19	.28	—			
6. Openness	31.18	5.84	-.07	-.09	.22	.17	.15	—		
7. Daily screen time (hours)	5.36	1.94	.41	.38	-.16	-.27	-.12	-.05	—	
8. Sleep regularity index	0.71	0.12	-.35	-.29	.18	.31	.14	.09	-.33	—

All correlations ≥ |.12| were statistically significant at $p < .05$.

As shown in Table 1, participants reported a moderate level of somatic complaints, with sufficient variability to support predictive modeling. Neuroticism exhibited a strong positive correlation with somatic complaints, indicating that individuals with higher emotional instability tended to report more frequent and intense physical symptoms. In contrast, conscientiousness and extraversion were negatively associated with somatic complaints, suggesting a potential protective role of self-regulation and social engagement. Among smartphone-derived indicators, daily screen time showed a substantial positive association with somatic complaints, whereas sleep regularity demonstrated a moderate negative association. These descriptive patterns provided an initial indication that both psychological traits and digital behavioral markers were meaningfully related to somatic symptom reporting and justified their joint inclusion in subsequent machine learning models.

Table 2

Predictive performance of machine learning models for somatic complaints

Model	RMSE	MAE	R^2
Multiple linear regression	5.92	4.61	.38
Lasso regression	5.74	4.43	.41
Random forest	4.89	3.71	.56
Gradient boosting	4.63	3.49	.61
Support vector regression	4.78	3.66	.58

Table 2 summarizes the predictive accuracy of the evaluated machine learning models on the held-out test set. Traditional multiple linear regression explained a modest proportion of variance in somatic complaints, reflecting the limitations of linear assumptions in capturing complex relationships between personality, behavior, and health-related outcomes. Regularized linear modeling via lasso regression yielded a small improvement, suggesting that feature shrinkage helped reduce noise and multicollinearity. Substantial gains in predictive performance were observed for nonlinear and ensemble-based models. The gradient boosting model achieved the best overall performance, explaining more than sixty percent of the variance in somatic complaints and yielding the lowest error indices. Random forest and support vector regression also demonstrated strong predictive capacity, outperforming linear approaches by a considerable margin. These findings indicate that somatic complaints are best understood as the outcome of nonlinear interactions among psychological traits and behavioral patterns rather than as a simple additive function of predictors.

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Table 3

Incremental predictive value of personality traits and smartphone-derived features

Predictor set	RMSE	R^2	ΔR^2
Personality traits only	5.48	.44	—
Smartphone data only	5.21	.49	—
Combined model	4.63	.61	.12

The results presented in Table 3 demonstrate the incremental value of integrating personality traits with smartphone-derived behavioral indicators. Models trained exclusively on personality traits achieved moderate predictive accuracy, underscoring the relevance of dispositional factors for somatic symptom reporting. Smartphone-derived behavioral data alone performed comparably, highlighting the capacity of passive digital markers to capture health-relevant behavioral patterns. Importantly, the combined model substantially outperformed both single-domain models, yielding a notable increase in explained variance. This incremental gain indicates that personality and behavioral data contribute unique, nonredundant information to the prediction of somatic complaints and that their integration offers a more comprehensive representation of individuals' psychosomatic functioning.

Table 4

Relative feature importance in the best-performing gradient boosting model

Feature	Relative importance
Neuroticism	0.24
Sleep regularity index	0.18
Daily screen time	0.16
Nighttime phone activity	0.11
Conscientiousness	0.09
Physical inactivity duration	0.08
Extraversion	0.07
App switching frequency	0.07

Table 4 presents the relative importance of the most influential predictors within the gradient boosting model. Neuroticism emerged as the single strongest predictor, reaffirming its central role in vulnerability to somatic complaints. Among behavioral indicators, sleep regularity and daily screen time showed particularly high importance, suggesting that dysregulated sleep–wake patterns and prolonged device use are key digital correlates of somatic symptom burden. Nighttime phone activity and physical inactivity duration further contributed to prediction accuracy, reflecting behavioral rhythms associated with fatigue and bodily discomfort. Personality traits such as conscientiousness and extraversion retained meaningful, albeit smaller, contributions, indicating that both stable dispositions and modifiable behaviors jointly shape somatic experiences.

Table 5

Model robustness across demographic subgroups

Subgroup	R^2	RMSE
Men	.59	4.71
Women	.62	4.58
Age 18–30	.63	4.49
Age 31–45	.60	4.66
Age 46–60	.57	4.88

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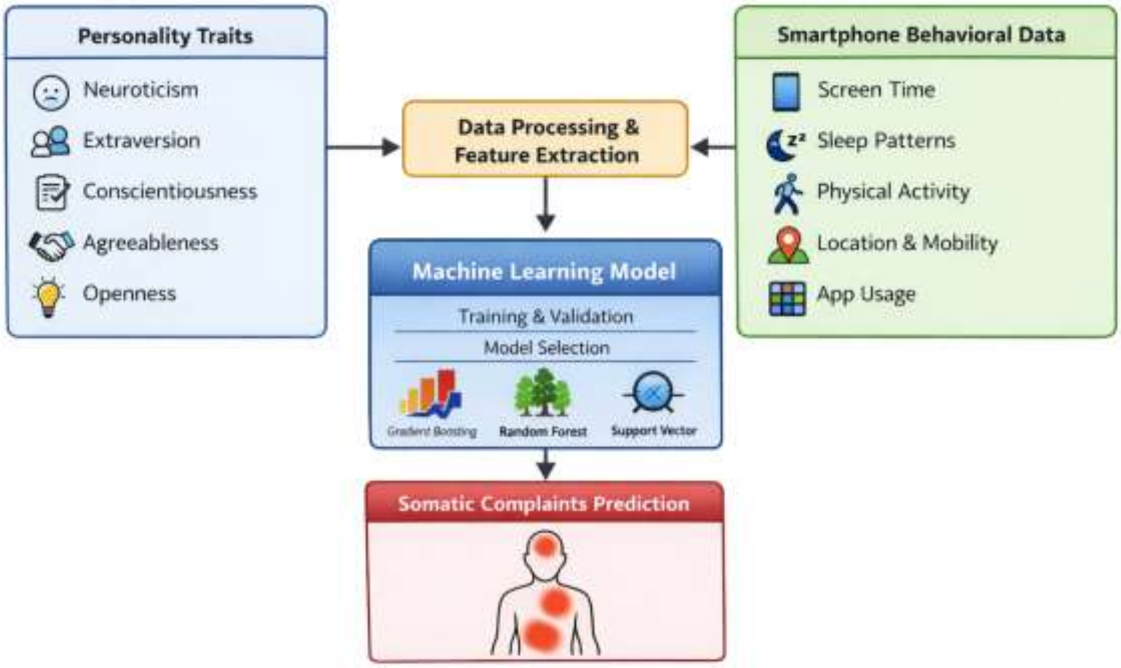
As shown in Table 5, the predictive performance of the best-performing model remained relatively stable across gender and age subgroups. Slightly higher accuracy was observed among younger participants, potentially reflecting greater consistency in smartphone usage patterns within this group. Nevertheless, the overall robustness of the model across demographic strata supports the generalizability of the findings and suggests that the predictive relationships identified are not confined to a specific subgroup within the Armenian sample.

Figure 1

Conceptual visualization of the integrated machine learning framework for predicting somatic complaints from personality traits and smartphone-derived behavioral data



4. Discussion and Conclusion

The present study sought to predict somatic complaints by integrating personality traits and smartphone-derived behavioral data within a machine learning framework, and the findings provide several important theoretical and empirical insights. Overall, the results demonstrated that models combining dispositional and behavioral indicators substantially outperformed models relying on a single data domain, underscoring the multifactorial nature of somatic complaints and supporting contemporary biopsychosocial perspectives. The superior performance of nonlinear and ensemble-based machine learning models further suggests that somatic complaints emerge from complex, interactive processes rather than from simple linear associations among predictors.

One of the most salient findings was the strong and consistent contribution of neuroticism to the prediction of somatic complaints. Across models, neuroticism emerged as the most influential personality trait, which aligns with a robust body of literature identifying neuroticism as a key vulnerability factor for both emotional and somatic distress. Individuals high in neuroticism tend to experience heightened negative affect, increased stress reactivity, and greater attentional focus on bodily sensations, all of which can amplify the perception and reporting of physical symptoms (Okutucu & Ceyhun, 2025; Zdanowicz et al., 2025). This finding is consistent with studies showing that neuroticism predicts a wide range of psychopathological and psychosomatic outcomes, including anxiety, depression, chronic pain, and reduced quality of life (Jacobs et al., 2022; Perlini, 2025). The present results extend this evidence by demonstrating that neuroticism retains its predictive importance even when dynamic behavioral indicators derived from smartphones are taken into account, highlighting its central role as a stable dispositional risk factor.

Conscientiousness and extraversion showed negative associations with somatic complaints and contributed modest but meaningful predictive value within the combined models. Higher conscientiousness has been linked to healthier daily routines, better self-regulation, and more adaptive coping strategies, which may buffer against stress-related somatic symptoms (Eren & Yiğitoğlu, 2023; Kakuta et al., 2024). Similarly, extraversion is often associated with greater social engagement and positive affect, factors that can mitigate symptom burden and reduce the likelihood of somatic preoccupation (Ferguson et al., 2022; Gashi et al., 2022). These findings are in line with previous research showing that protective personality traits are associated with lower levels of emotional and physical complaints, particularly in stressful contexts (Damian et al., 2023; Gong et al., 2023). Importantly, the relatively smaller effect sizes of these traits compared to neuroticism suggest that protective dispositions may operate indirectly, partly through their influence on daily behaviors captured by smartphone-derived indicators.

Beyond personality, smartphone-derived behavioral data emerged as powerful predictors of somatic complaints. Among these indicators, sleep regularity and daily screen time were particularly influential. Irregular sleep–wake patterns and excessive screen time have been consistently associated with fatigue, somatic discomfort, and stress-related symptoms, both in clinical and nonclinical populations (Srivastava et al., 2025; Su et al., 2024). The present findings corroborate this literature and demonstrate that passive digital markers of sleep and usage rhythms provide meaningful information about somatic health. These results are also consistent with digital phenotyping studies showing that disrupted circadian patterns and prolonged device use are associated with poorer mental and physical well-being (Asare et al., 2022; Müller-Bardorff et al., 2024).

Nighttime phone activity and physical inactivity duration further contributed to model performance, suggesting that not only the quantity but also the timing and structure of smartphone use are relevant for understanding somatic complaints. Nighttime phone use may interfere with sleep quality and recovery processes, thereby exacerbating physical symptoms such as fatigue and pain (Song, 2025; Turan & Yılmaz, 2024). Similarly, prolonged periods of inactivity inferred from smartphone sensors may reflect sedentary lifestyles or low energy levels, both of which have been linked to increased somatic symptom reporting (Grover, 2022; Vroegindeweij et al., 2023). These findings support the notion that smartphone-derived behavioral data capture ecologically valid indicators of daily functioning that are closely tied to physical symptom experiences.

A key contribution of this study lies in demonstrating the incremental predictive value of integrating personality traits with smartphone-derived behavioral indicators. Models that combined both data sources explained substantially more variance in somatic complaints than models relying on personality or behavioral data alone. This result aligns with meta-analytic evidence indicating that while smartphone data can predict certain psychological traits and states, their predictive accuracy improves when combined with self-reported psychological measures (Marengo et al., 2023). From a theoretical standpoint, this integration reflects the interplay between stable dispositions and situationally embedded behaviors. Personality traits shape how individuals interact with their digital environment, while smartphone-derived behaviors provide real-time manifestations of these dispositions under everyday conditions (Rodríguez et al., 2025; Venkateswaran et al., 2025). The present findings suggest that somatic complaints are best understood through such integrative models rather than through isolated predictors.

The superior performance of gradient boosting and other ensemble-based machine learning models further underscores the complexity of the relationships among personality, behavior, and somatic symptoms. Traditional linear models captured only a limited portion of variance, whereas nonlinear approaches were able to model interactions and threshold effects more effectively. This is consistent with prior research in mental health prediction, where machine learning methods have outperformed conventional statistical approaches in predicting depression, anxiety, and fatigue-related outcomes (Chung & Park, 2025; Fuller et al., 2025). The findings also resonate with analytical approaches emphasizing the importance of detecting nonlinear trends and unexpected behavioral changes in psychological time series (Parpoula, 2024). Together, these results highlight the methodological value of machine learning for advancing psychosomatic research in the era of digital data.

The robustness of the predictive models across gender and age subgroups suggests that the identified relationships are relatively stable within the studied population. This finding is noteworthy given evidence that symptom expression and technology use can vary across demographic groups (Bhayangkara et al., 2024; Zhao et al., 2024). While slight differences in predictive accuracy were observed across age groups, the overall consistency supports the generalizability of the integrative modeling approach. This robustness aligns with previous studies demonstrating that

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personality–health relationships persist across demographic contexts, even when the specific behavioral expressions may differ (Aksnes et al., 2024; Gashi et al., 2022).

From a broader perspective, the present findings contribute to the growing literature on digital mental and physical health by extending predictive modeling beyond emotional disorders to somatic complaints. While many previous studies have focused on depression, anxiety, or problematic smartphone use, somatic symptoms have received comparatively less attention despite their high prevalence and clinical relevance (Hoshino et al., 2023; Ibrar et al., 2023). By demonstrating that somatic complaints can be effectively predicted using a combination of personality traits and passive behavioral data, this study provides empirical support for expanding digital phenotyping approaches to psychosomatic outcomes.

Despite its strengths, this study has several limitations that should be acknowledged. First, the cross-sectional design limits causal inferences regarding the directionality of the observed relationships between personality, smartphone behaviors, and somatic complaints. Second, although smartphone-derived data provide objective behavioral indicators, they may not fully capture contextual factors such as occupational demands or social stressors that influence somatic symptoms. Third, the reliance on a single cultural context may limit the generalizability of the findings to other populations with different technology use patterns and health norms. Finally, while machine learning models demonstrated strong predictive performance, their interpretability remains limited compared to traditional statistical models.

Future studies should adopt longitudinal designs to examine how changes in smartphone-derived behaviors and personality-related processes predict trajectories of somatic complaints over time. Incorporating ecological momentary assessments could further enhance the temporal resolution of symptom measurement. Expanding research to diverse cultural and clinical populations would improve generalizability and allow for cross-cultural comparisons. Additionally, integrating physiological data from wearables, such as heart rate variability or sleep stages, may further enhance predictive accuracy and deepen understanding of underlying mechanisms.

From a practical standpoint, the findings highlight the potential of combining personality assessment with passive smartphone monitoring to identify individuals at risk for elevated somatic complaints. Such integrative approaches could support early screening and personalized interventions in preventive healthcare settings. Clinicians and health practitioners may use insights from digital behavior patterns to tailor recommendations related to sleep hygiene, smartphone use, and daily routines. Moreover, the application of machine learning models in digital health platforms could facilitate scalable, low-burden monitoring of somatic well-being in everyday life.

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

The authors report no conflict 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.

References

Aksnes, E. R., Birkeland, M. S., Ebrahimi, O. V., Bekkhus, M., Ferschmann, L., Beck, D., Fixdal, T., Havdahl, A., Speyer, L. G., Westlye, L. T., Bos, M. G., & Tamnes, C. K. (2024). Development of Symptoms of Emotional Problems From Childhood to Adolescence: A Longitudinal Network Analysis. https://doi.org/10.31219/osf.io/m5gr7_v1

Asare, K. O., Visuri, A., Vega, J., & Ferreira, D. (2022). Me In the Wild: An Exploratory Study Using Smartphones To Detect The Onset Of Depression. 121-145. https://doi.org/10.1007/978-3-031-06368-8_9

Bhayangkara, N. I., Lerik, M. D. C., & Benu, J. M. Y. (2024). Smartphone Addiction Reviewed From Big Five Personality in College Students. *Journal of Health and Behavioral Sciences*, *6*(4), 426-437. https://doi.org/10.35508/jhbs.v6i4.15601

Chung, K., & Park, J. Y. (2025). Identifying Subgroups at Risk for Major Depression and Suicidal Ideation via Mobile App–Based Ecological Momentary Assessment: A Cluster Analysis (Preprint). https://doi.org/10.2196/preprints.80332

Damian, A., Mihăilescu, A., Anghele, C., Ciobanu, C. A., Petrescu, C., Riga, S., Dionisie, V., & Ciobanu, A. M. (2023). Quality of Life Predictors in a Group of Informal Caregivers During the COVID-19 Pandemic. *Medicina*, *59*(8), 1486. https://doi.org/10.3390/medicina59081486

Eren, N., & Yiğitoğlu, G. T. (2023). Delirium Awareness and Management of Intensive Care Nurses in Terms of Their Personality Traits. *Ordu Üniversitesi Hemşirelik Çalışmaları Dergisi*, *6*(2), 393-403. https://doi.org/10.38108/ouhcd.1128273

Ferguson, G., Pasquini, G., Sliwinski, M. J., & Scott, S. (2022). Measuring Personality in Daily Life: Evidence From an Age-Heterogeneous Adult Sample. *Innovation in Aging*, *6*(Supplement_1), 641-641. https://doi.org/10.1093/geroni/igac059.2374

Fuller, C., Marin-Dragu, S., Iyer, R. S., & Meier, S. (2025). A Mobile App–Based Gratitude Intervention's Effect on Mental Well-Being in University Students: Randomized Controlled Trial. *Jmir Mhealth and Uhealth*, *13*, e53850-e53850. https://doi.org/10.2196/53850

Gashi, D., Gallopeni, F., Imeri, G., Shahini, M., & Bahtiri, S. (2022). The Relationship Between Big Five Personality Traits, Coping Strategies, and Emotional Problems Through the COVID-19 Pandemic. *Current Psychology*, *42*(33), 29179-29188. https://doi.org/10.1007/s12144-022-03944-9

Gong, F., Jia, Y., Sun, X., Min, H., Jia, X., Wang, F., Huang, X., Lin, X., Li, Z., & Wu, Y. (2023). The Influence of Media Use Degree on Public Depressive Symptoms: Mediating Role of Big Five Personality. *BMC psychiatry*, *23*(1). https://doi.org/10.1186/s12888-023-05097-w

Grover, S. (2022). Loneliness Among the Elderly: A Mini Review. *Consortium Psychiatricum*, *3*(1), 30-36. https://doi.org/10.17816/cp143

Hoshino, Y., Kataoka, S., & Ansai, T. (2023). Association of Personality Traits With Dental Visit Procrastination by Japanese University Students. *BioPsychoSocial Medicine*, *17*(1). https://doi.org/10.1186/s13030-023-00288-z

Ibrar, K., Fayyaz, A. M., Khan, M. A., Alhaisoni, M., Tariq, U., Jeon, S., & Nam, Y. (2023). Human Personality Assessment Based on Gait Pattern Recognition Using Smartphone Sensors. *Computer Systems Science and Engineering*, *46*(2), 2351-2368. https://doi.org/10.32604/csse.2023.036185

Jacobs, P., Wagner, M. F., Paloski, L. H., Irani Iracema de Lima, A., & Oliveira, C. R. d. (2022). Personality Traits and Psychopathological Symptoms in Adults With Substance Use Disorders. *Behavioral Psychology/Psicología Conductual*, *30*(2), 347-357. https://doi.org/10.51668/bp.8322201n

Kakuta, M., Gondo, Y., Nakagawa, T., Masui, Y., Kamide, K., Ikebe, K., Ishizaki, T., & Arai, Y. (2024). Relationship Between Personality Traits and Preference for Coping Styles in Older Adults. *Innovation in Aging*, *8*(Supplement_1), 770-770. https://doi.org/10.1093/geroni/igae098.2503

Marengo, D., Elhai, J. D., & Montag, C. (2023). Predicting Big Five Personality Traits From Smartphone Data: A Meta-analysis on the Potential of Digital Phenotyping. *Journal of personality*, *91*(6), 1410-1424. https://doi.org/10.1111/jopy.12817

Müller-Bardorff, M., Schulz, A., Paersch, C., Recher, D., Schlup, B., Seifritz, E., Kolassa, I. T., Kowatsch, T., Fisher, A. J., Galatzer-Levy, I. R., & Kleim, B. (2024). Optimizing Outcomes in Psychotherapy for Anxiety Disorders Using Smartphone-Based and Passive Sensing Features: Protocol for a Randomized Controlled Trial. *Jmir Research Protocols*, *13*, e42547. https://doi.org/10.2196/42547

Okutucu, F. T., & Ceyhun, H. A. (2025). The Impact of Anxiety and Depression Levels on the Big Five Personality Traits. *PLoS One*, *20*(7), e0321373. https://doi.org/10.1371/journal.pone.0321373

Parpoula, C. (2024). An Analytical Approach for Identifying Trend-seasonal Components and Detecting Unexpected Behaviour in Psychological Time-series. *International journal of psychology*, *59*(6), 1307-1316. https://doi.org/10.1002/ijop.13244

Perlini, C. (2025). Psycho-Social Profile of Patients With Chronic Neuropathic Pain and Spinal Cord Stimulation Outcome: Preliminary Finding From an Italian Sample Recruited at the University Hospital of Verona (Italy). *European Psychiatry*, *68*(S1), S936-S936. https://doi.org/10.1192/j.eurpsy.2025.1897

Rodríguez, B. C., Rodríguez-Sedano, F. J., & Porras-García, E. (2025). Assessing Vulnerability to Harmful Internet, Social Media, and Digital Environment Use Through the Big Five Model: A Neuropsychosocial Perspective. https://doi.org/10.20944/preprints202510.1542.v1

Song, H. (2025). Integrating Ecological Momentary Assessment and Intervention With Wearable-Based Digital Phenotypes for Anxiety in Young Adults: A Mixed-Method Experimental Study (Preprint). https://doi.org/10.2196/preprints.88919

Srivastava, S., Verma, N., Kumar, D., Singh, N., & Kumar, K. (2025). Nomophobia as an Emerging Psychopathology Psychophysiological Mechanisms and Clinical Implications. *Annals of Neurosciences*. https://doi.org/10.1177/09727531251351082

Su, S., Cousijn, J., Molenaar, D., Freichel, R., Larsen, H., & Wiers, R. W. (2024). From Everyday Life to Measurable Problematic Smartphone Use: The Development and Validation of the Smartphone Use Problems Identification Questionnaire (SUPIQ). *Journal of Behavioral Addictions*, *13*(2), 506-524. https://doi.org/10.1556/2006.2024.00010

Turan, Z., & Yılmaz, R. M. (2024). Do Personality Traits Influence Nomophobia? An Investigation of the Big Five Personality Traits and Nomophobia Levels in University Students. *Psycho-Educational Research Reviews*, *13*(1). https://doi.org/10.52963/perr_biruni_v13.n1.03

Venkateswaran, P. S., Rekha, N., & Sriramkumar, M. (2025). A Study on the Relationship Between Personality Traits and Levels of Smartphone Addiction to Gain Insights Into Sales Executive Behavioral Patterns. 303-336. https://doi.org/10.4018/979-8-3693-8804-4.ch011

Vroegindeweij, A., Swart, J. F., Houtveen, J., Eijkelkamp, N., Elise, M. v. d. P., Wulffraat, N., & Nijhof, S. L. (2022). Identifying Disrupted Biological Factors and Patient-Tailored Interventions for Chronic Fatigue in Adolescents and Young Adults With Q-Fever Fatigue Syndrome, Chronic Fatigue Syndrome and Juvenile Idiopathic Arthritis (QFS-study): Study Protocol for a Randomized Controlled Trial With Single-Subject Experimental Case Series Design. *Trials*, *23*(1). https://doi.org/10.1186/s13063-022-06620-2

Vroegindeweij, A., Wulffraat, N., Elise, M. V. D. P., Hanne, B. T. d. J., Lucassen, D. A., Swart, J. F., & Nijhof, S. L. (2023). Targeting Persistent Fatigue With Tailored Versus Generic Self-management Strategies in Adolescents and Young Adults With a Fatigue Syndrome or Rheumatic Condition: A

JPPR
E-ISSN: 3041-8542

Randomized Crossover Trial. *British Journal of Health Psychology*, *29*(3), 516-532. https://doi.org/10.1111/bjhp.12711

Zdanowicz, P., Pasieka, Z., Wujcik, R., Kamola, P. J., Białas, A. J., & Pietras, T. (2025). Structure of Patients' Temperament Traits as a Risk Factor for Anxiety and Depression in Patients With Asthma and Chronic Obstructive Pulmonary Disease (COPD). *Journal of clinical medicine*, *14*(10), 3414. https://doi.org/10.3390/jcm14103414

Zhao, L., Gooi, L.-M., & Wang, L. (2024). The Relationship Between Personality Traits and Turnover Intention of Private University Teachers: The Mediating Role of Sense of Belonging. *Academic Journal of Management and Social Sciences*, *8*(2), 137-148. https://doi.org/10.54097/r7hgps38

JPPR
E-ISSN: 3041-8542