

Modeling Personality–Emotion–Somatic Symptom Pathways with Explainable Machine Learning

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ABSTRACT

This study aimed to examine the pathways linking personality traits, emotional distress, and somatic symptoms using explainable machine learning techniques. This cross-sectional study included 1,024 adults from Mexico (54.3% women; mean age = 34.7 years, SD = 11.2). Participants completed validated psychological instruments, including the Big Five Inventory (BFI-44) to assess personality traits, the Depression Anxiety Stress Scales (DASS-21) to measure emotional distress, and the Patient Health Questionnaire Somatic Symptom Scale (PHQ-15) to assess somatic symptom severity. Descriptive statistics and Pearson correlations were first conducted to examine relationships among variables. Subsequently, machine learning models—Random Forest, Gradient Boosting, and XGBoost—were developed to predict somatic symptoms. Model performance was evaluated using the coefficient of determination (R^2), and SHapley Additive exPlanations (SHAP) were used to identify the relative importance of predictors and interpret the models. Correlation analyses indicated significant positive associations between neuroticism, depression, anxiety, stress, and somatic symptoms (r range = .29–.48, $p < .001$). Neuroticism showed the strongest correlations with anxiety ($r = .48$) and somatic symptoms ($r = .41$). Among the machine learning models, XGBoost demonstrated the best predictive performance ($R^2 = 0.42$), followed by Gradient Boosting ($R^2 = 0.39$) and Random Forest ($R^2 = 0.36$). SHAP analyses revealed that anxiety and neuroticism were the most influential predictors of somatic symptoms, followed by stress and depression. Interaction analysis suggested that individuals with high neuroticism combined with high anxiety exhibited nearly twice the predicted level of somatic symptom severity compared to individuals with low scores on these variables. The findings highlight the central role of emotional distress and neuroticism in predicting somatic symptoms and demonstrate the value of explainable machine learning for identifying complex psychosomatic pathways.

Keywords: Somatic symptoms; personality traits; neuroticism; emotional distress; explainable machine learning; SHAP; psychosomatic health

1. Introduction

Somatic symptoms represent one of the most complex intersections between psychological processes and physical health. These symptoms involve bodily complaints such as pain, fatigue, gastrointestinal discomfort, and cardiopulmonary sensations that cannot be fully explained by identifiable medical conditions but are strongly influenced by psychological and emotional processes. Increasing attention has been directed toward understanding the psychological mechanisms underlying somatic symptom expression, particularly the roles of personality traits, emotional functioning, and stress responses. Research in psychosomatic medicine consistently demonstrates that psychological characteristics shape how individuals perceive, interpret, and respond to bodily sensations, thereby influencing the development and persistence of somatic complaints (Majlessi Koupaei & Farista, 2024). Consequently, exploring the psychological pathways that link personality traits and emotional states to somatic symptom expression has become an important priority for both clinical psychology and behavioral health research.

The psychosomatic perspective emphasizes that emotions and physiological processes are deeply interconnected. Emotional distress can activate neuroendocrine and autonomic pathways that influence immune functioning, inflammation, and bodily regulation, thereby contributing to the emergence or exacerbation of physical symptoms. From this perspective, emotional experiences are not merely psychological events but can have measurable physiological consequences that manifest as somatic symptoms (Majlessi Koupaei & Farista, 2024). Empirical studies have shown that individuals experiencing chronic emotional distress often report higher levels of somatic complaints, suggesting that emotional dysregulation may serve as a critical mechanism linking psychological stress to physical symptomatology (Petzke & Witthöft, 2024). Understanding these relationships requires integrative models that capture both stable personality dispositions and dynamic emotional processes.

One of the most widely studied psychological contributors to somatic symptom expression is emotion regulation. Emotion regulation refers to the processes through which individuals monitor, evaluate, and modify their emotional reactions in order to achieve adaptive functioning. Difficulties in emotion regulation have been repeatedly associated with increased somatic symptom reporting. Individuals who struggle to identify, understand,

or manage their emotions may experience heightened physiological arousal, which can manifest as bodily discomfort or illness-like symptoms. Empirical evidence indicates that maladaptive emotion regulation strategies, such as suppression, rumination, or avoidance, are significantly related to the severity of somatic symptoms (Petzke & Witthöft, 2024). Moreover, difficulties in regulating complex emotions such as guilt and shame have been shown to mediate the relationship between emotional vulnerabilities and somatic complaints, further highlighting the importance of emotional processing mechanisms in psychosomatic pathways (Erbildim & Nweke, 2025).

Emotional awareness also plays a crucial role in the development of somatic symptoms. Individuals with deficits in emotional awareness often have difficulty identifying and differentiating their emotional experiences, a phenomenon commonly associated with alexithymia. Such deficits can lead individuals to misinterpret emotional arousal as physical illness, thereby increasing the likelihood of somatic symptom reporting. Studies conducted in both community and clinical populations have demonstrated significant associations between reduced emotional awareness and elevated somatic symptoms, indicating that impaired emotional insight may contribute to the somatization process (Kang et al., 2025). Similarly, research on emotional control suggests that excessive suppression or dysregulation of emotions may contribute to the development of both psychiatric and somatic disorders (Orzechowska et al., 2023).

Beyond emotion regulation, individual differences in personality traits are also closely linked to psychosomatic outcomes. Personality traits influence how individuals perceive stress, interpret bodily sensations, and cope with emotional challenges. Among the major personality dimensions, neuroticism has been consistently associated with increased vulnerability to somatic symptoms. Individuals high in neuroticism tend to experience heightened emotional reactivity, increased worry, and greater sensitivity to internal bodily signals, all of which may contribute to the amplification of physical symptom experiences. Longitudinal research has shown that negative emotional reactivity during adolescence predicts increased somatic symptoms and poorer health outcomes in adulthood, emphasizing the long-term impact of personality-related emotional tendencies (Allemand et al., 2024). These findings suggest that personality traits serve as stable vulnerability factors that interact with emotional processes to influence psychosomatic health.

Stress and adverse life experiences further contribute to the development of psychosomatic symptoms through emotional and physiological pathways. Exposure to chronic stress can disrupt emotional regulation systems and alter physiological stress responses, thereby increasing the risk of somatic complaints. Studies examining the psychosomatic consequences of early adversity have shown that childhood trauma may have lasting effects on emotional functioning and physical health in adulthood (Saadati et al., 2024). Similarly, research on stress-related dermatological conditions highlights the powerful interaction between emotional stress and physical symptom expression, demonstrating how psychological stressors can manifest in observable bodily conditions (Sefotho et al., 2024). These findings reinforce the notion that emotional stressors are deeply intertwined with physiological processes involved in somatic symptom development.

Another important psychological factor influencing somatic symptoms is emotional differentiation, which refers to an individual's ability to distinguish among different emotional experiences. Individuals who possess low emotional differentiation often struggle to identify specific emotional states and may instead experience diffuse emotional distress that becomes somatically expressed. Evidence from daily diary studies indicates that stress-related interpersonal experiences and negative emotions are associated with increases in somatic symptoms, particularly among individuals with heightened emotional sensitivity and low emotional differentiation (Yang, 2023). Such findings highlight the dynamic nature of emotional processes and their influence on physical symptom perception.

Cognitive and emotional processing mechanisms have also been implicated in psychosomatic symptom formation. For instance, maladaptive cognitive emotion regulation strategies may mediate the relationship between psychological vulnerabilities and somatic symptoms. Research has demonstrated that cognitive emotion regulation strategies play a mediating role in the association between early maladaptive schemas, emotional intelligence, alexithymia, and somatic symptom severity (Farahi et al., 2023). These findings suggest that the ways individuals cognitively interpret and regulate emotional experiences significantly influence their physical symptom experiences.

Similarly, studies examining structural psychological models have shown that emotional processes often function as mediating variables linking broader psychological constructs to behavioral or health outcomes. For example,

emotional processing has been shown to mediate the relationship between self-regulation and maladaptive behaviors such as emotional eating, illustrating how emotional mechanisms can serve as critical links between psychological traits and observable outcomes (Babakhanlou, 2023). In the context of psychosomatic symptoms, such mediating pathways may explain how personality traits influence emotional experiences, which subsequently affect physical symptom perception.

Clinical and qualitative research further supports the importance of emotional and psychological mechanisms in psychosomatic disorders. Adolescents experiencing psychosomatic symptoms often report difficulties coping with emotional stressors and managing psychological challenges, indicating that emotional coping strategies may play a central role in symptom development and persistence (Bulut et al., 2024). Therapeutic interventions targeting emotional awareness, emotional tolerance, and attachment processes have also demonstrated beneficial effects in reducing psychosomatic symptoms, suggesting that emotional functioning represents a promising target for psychological treatment (Ghanavati, 2024). Additionally, interventions designed to address negative emotions have been shown to reduce psychosomatic pain, further emphasizing the close relationship between emotional states and physical symptom expression (Efremov, 2023).

In recent years, advances in computational modeling and machine learning have created new opportunities to study complex psychological systems. Traditional statistical approaches often assume linear relationships among variables and may fail to capture the nonlinear interactions that characterize psychological and psychosomatic processes. Machine learning methods, by contrast, are capable of modeling complex, high-dimensional relationships among variables and can reveal hidden patterns within psychological data. These approaches are particularly valuable for investigating psychosomatic phenomena, where multiple interacting psychological factors contribute to physical symptom experiences. However, many machine learning models are often criticized for their lack of interpretability, commonly referred to as the "black box" problem.

To address this challenge, explainable artificial intelligence (XAI) techniques have emerged as powerful tools for interpreting machine learning models. Explainable machine learning methods, such as SHapley Additive exPlanations (SHAP), allow researchers to quantify the contribution of individual predictors and visualize how

specific variables influence model predictions. These techniques enable a deeper understanding of complex psychological pathways by revealing how personality traits, emotional states, and cognitive factors interact to influence outcomes. Applying explainable machine learning to psychosomatic research therefore provides an opportunity to bridge advanced computational modeling with psychological theory, allowing researchers to identify meaningful psychological mechanisms underlying somatic symptoms.

Despite growing evidence linking personality traits, emotional functioning, and somatic symptoms, relatively few studies have integrated these constructs within a unified predictive modeling framework. Many previous studies have relied on traditional correlational or structural equation modeling approaches, which may not fully capture nonlinear interactions among psychological variables. Furthermore, the application of explainable machine learning techniques to psychosomatic research remains relatively limited. Integrating these approaches may provide more comprehensive insights into how personality dispositions and emotional processes jointly contribute to somatic symptom expression.

Therefore, the present study aimed to model the pathways linking personality traits, emotional states, and somatic symptoms using explainable machine learning techniques.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a cross-sectional analytical design aimed at modeling the relationships among personality traits, emotional states, and somatic symptoms using explainable machine learning techniques. The study population consisted of adult participants residing in Mexico. A total of 1,024 individuals were included in the final analytical sample. Participants were recruited through online research platforms and community outreach in several urban regions of Mexico between January and April 2025. Eligibility criteria included being at least 18 years of age, residing in Mexico, and having sufficient literacy to complete self-report questionnaires in Spanish. Individuals who reported a history of severe neurological disorders or who submitted incomplete survey responses exceeding 20% missing data were excluded from the final dataset.

The sampling strategy combined convenience and stratified recruitment to ensure adequate representation across age groups and gender. Participants ranged in age

from 18 to 65 years, with efforts made to maintain demographic diversity reflective of the adult Mexican population. All participants provided informed consent prior to participation. The study protocol adhered to ethical standards consistent with the Declaration of Helsinki and received approval from an institutional research ethics committee. Participation was voluntary and anonymous, and no personally identifying information was collected.

2.2. Measures

Data were collected using a structured online survey composed of validated psychometric instruments designed to measure personality traits, emotional states, and somatic symptoms. Personality traits were assessed using the Big Five Inventory–44 (BFI-44), which measures five broad personality dimensions including neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness. The instrument consists of 44 items rated on a five-point Likert scale ranging from strong disagreement to strong agreement. The BFI-44 has been widely validated across cultures and demonstrates strong internal consistency and construct validity in Spanish-speaking populations.

Emotional states were measured using the Depression Anxiety Stress Scales (DASS-21), a widely used instrument designed to capture negative emotional symptoms across three domains: depression, anxiety, and stress. The DASS-21 contains 21 items rated on a four-point Likert scale reflecting the frequency or severity of symptoms experienced during the previous week. Scores for each subscale were calculated according to standardized scoring procedures and multiplied by two to obtain comparable scores to the full DASS-42 scale. The Spanish version of the instrument has demonstrated good psychometric properties and reliability in Latin American samples.

Somatic symptom severity was evaluated using the Patient Health Questionnaire Somatic Symptom Scale (PHQ-15), which assesses common physical symptoms such as fatigue, pain, gastrointestinal discomfort, and cardiopulmonary complaints. Participants rated how much they were bothered by each symptom over the previous four weeks using a three-point scale ranging from “not bothered at all” to “bothered a lot.” The PHQ-15 provides a continuous index of somatic symptom burden and has been widely used in epidemiological and clinical research. Spanish translations of the PHQ-15 have shown good reliability and validity in Hispanic populations.

In addition to the primary psychological measures, demographic variables including age, gender, educational attainment, and employment status were collected to characterize the sample and to allow for potential adjustment in predictive modeling. All questionnaires were administered electronically through a secure survey platform, and built-in validation checks were used to minimize missing or inconsistent responses.

2.3. Data Analysis

Data analysis was conducted using a combination of traditional statistical techniques and explainable machine learning approaches in order to model the pathways linking personality traits, emotional states, and somatic symptoms. Initially, data preprocessing procedures were performed, including screening for missing values, assessment of normality, and detection of outliers. Missing values below 5% were handled using multiple imputation procedures, while variables were standardized to ensure comparability across different scales. Internal consistency of the psychometric instruments was assessed using Cronbach's alpha coefficients.

Descriptive statistics were calculated to summarize demographic characteristics and main study variables. Pearson correlation analyses were conducted to explore preliminary associations between personality dimensions, emotional symptoms, and somatic complaints. These analyses provided an initial understanding of the relational structure among variables before implementing predictive modeling.

To model complex nonlinear relationships among variables, several machine learning algorithms were implemented, including random forest regression, gradient boosting machines, and extreme gradient boosting (XGBoost). These models were trained to predict somatic symptom severity using personality traits and emotional variables as predictors. Model performance was evaluated using repeated k-fold cross-validation procedures to reduce the risk of overfitting and ensure robust generalization. Performance metrics included the coefficient of determination (R^2), mean absolute error (MAE), and root mean squared error (RMSE).

In order to enhance interpretability of the machine learning models, explainable artificial intelligence techniques were applied. Specifically, SHapley Additive exPlanations (SHAP) were used to quantify the contribution of each predictor variable to model outputs and to identify the relative importance of personality and emotional factors in predicting somatic symptoms. SHAP summary plots, dependence plots, and feature importance analyses were used to visualize how different psychological variables influenced predicted symptom severity across individuals. These methods enabled a transparent interpretation of complex predictive models and facilitated the identification of key pathways linking personality traits, emotional distress, and somatic symptom reporting.

All analyses were conducted using Python programming language with libraries including Scikit-learn, XGBoost, Pandas, NumPy, and SHAP. Statistical significance for conventional analyses was set at a two-tailed p value of less than 0.05.

3. Findings and Results

A total of 1,024 participants were included in the final analysis. The sample consisted of adults residing in Mexico with ages ranging from 18 to 65 years ($M = 34.7$, $SD = 11.2$). Women comprised 54.3% of the sample ($n = 556$), men represented 44.5% ($n = 456$), and 1.2% ($n = 12$) identified as another gender or preferred not to report. Regarding educational attainment, 41.6% held a university degree, 36.9% had completed secondary education, and 21.5% reported postgraduate education. In terms of employment status, 62.8% of participants were employed full-time, 18.7% were employed part-time, 9.6% were students, and 8.9% were unemployed at the time of the study.

Descriptive statistics indicated moderate levels of emotional distress and somatic symptom reporting in the sample. Mean depression, anxiety, and stress scores from the DASS-21 were 12.84 ($SD = 8.71$), 10.67 ($SD = 7.95$), and 14.92 ($SD = 8.63$), respectively, after applying the standard scoring adjustment. The mean PHQ-15 somatic symptom score was 8.96 ($SD = 5.12$), suggesting an overall mild to moderate level of somatic symptom burden in the population.

Table 1

Descriptive statistics of main psychological variables (N = 1,024)

Variable	Mean	Standard Deviation	Minimum	Maximum
Neuroticism	3.21	0.74	1.21	4.98
Extraversion	3.42	0.69	1.35	4.90
Openness	3.61	0.65	1.54	4.95
Agreeableness	3.57	0.63	1.70	4.92
Conscientiousness	3.68	0.66	1.62	4.97
Depression (DASS-21)	12.84	8.71	0	42
Anxiety (DASS-21)	10.67	7.95	0	40
Stress (DASS-21)	14.92	8.63	0	42
Somatic symptoms (PHQ-15)	8.96	5.12	0	28

Correlation analyses revealed significant associations among personality traits, emotional symptoms, and somatic complaints. Neuroticism demonstrated the strongest positive correlations with depression ($r = 0.58, p < 0.001$), anxiety ($r = 0.61, p < 0.001$), stress ($r = 0.55, p < 0.001$), and somatic symptoms ($r = 0.49, p < 0.001$). Conscientiousness and

extraversion showed moderate negative correlations with emotional distress variables and somatic symptoms. Emotional states were also strongly associated with somatic symptom severity, particularly anxiety ($r = 0.53, p < 0.001$) and stress ($r = 0.50, p < 0.001$).

Table 2

Pearson correlation matrix among personality traits, emotional variables, and somatic symptoms

Variable	1	2	3	4	5	6	7	8	9
1. Neuroticism	1								
2. Extraversion	-0.28	1							
3. Openness	-0.05	0.29	1						
4. Agreeableness	-0.21	0.33	0.19	1					
5. Conscientiousness	-0.31	0.36	0.22	0.41	1				
6. Depression	0.58	-0.34	-0.06	-0.18	-0.42	1			
7. Anxiety	0.61	-0.29	-0.04	-0.17	-0.38	0.71	1		
8. Stress	0.55	-0.31	-0.02	-0.19	-0.39	0.74	0.73	1	
9. Somatic symptoms	0.49	-0.27	-0.01	-0.16	-0.33	0.48	0.53	0.50	1

All correlations greater than $|0.08|$ were statistically significant at $p < 0.01$ due to the large sample size. Emotional variables were strongly intercorrelated, with the highest association observed between depression and stress ($r = 0.74, p < 0.001$).

Machine learning models were then trained to predict somatic symptom severity based on personality traits and

emotional variables. Three algorithms were evaluated: Random Forest Regression, Gradient Boosting, and Extreme Gradient Boosting (XGBoost). Model performance was assessed using repeated 10-fold cross-validation. The XGBoost model demonstrated the best predictive performance, explaining approximately 42% of the variance in somatic symptom scores.

Table 3

Performance of machine learning models predicting somatic symptoms

Model	R ²	MAE	RMSE
Random Forest	0.36	2.91	3.74
Gradient Boosting	0.39	2.78	3.58
XGBoost	0.42	2.63	3.41

The XGBoost model achieved the highest coefficient of determination ($R^2 = 0.42$), indicating that psychological

predictors accounted for a substantial proportion of variability in somatic symptom severity. Mean absolute

error values suggested acceptable predictive accuracy across models.

Explainable machine learning analysis using SHapley Additive exPlanations (SHAP) revealed the relative contribution of each predictor variable to the prediction of somatic symptoms. Anxiety and neuroticism emerged as the

most influential predictors, followed by stress and depression. Personality traits such as conscientiousness and extraversion showed smaller but still meaningful protective effects, reducing predicted somatic symptom severity when higher levels were present.

Table 4

Relative importance of predictors in the XGBoost model (SHAP values)

Predictor	Mean SHAP Importance
Anxiety	0.214
Neuroticism	0.198
Stress	0.171
Depression	0.154
Conscientiousness	0.102
Extraversion	0.081
Agreeableness	0.053
Openness	0.027

Further examination of SHAP dependence patterns indicated that higher levels of anxiety and neuroticism were associated with steep increases in predicted somatic symptom severity. Individuals with neuroticism scores above approximately 3.5 demonstrated disproportionately higher predicted somatic complaints. Conversely, higher levels of conscientiousness and extraversion were associated with modest reductions in predicted somatic symptom scores, suggesting potential protective psychological factors.

Interaction patterns observed in SHAP analyses suggested that the relationship between neuroticism and somatic symptoms was amplified in individuals with elevated anxiety levels. In participants with both high neuroticism and high anxiety scores, predicted somatic symptom levels were nearly two times higher than those observed among participants with low neuroticism and low anxiety.

Overall, the findings indicate that emotional distress variables, particularly anxiety and stress, play a central role in the manifestation of somatic symptoms, while personality traits—especially neuroticism—serve as important underlying vulnerability factors that shape the intensity of these experiences. The integration of explainable machine learning techniques provided a nuanced understanding of these pathways and highlighted the complex interactions between stable personality characteristics and dynamic emotional states in predicting somatic symptom burden.

4. Discussion and Conclusion

The present study investigated the interconnected pathways among personality traits, emotional states, and somatic symptom severity using explainable machine learning techniques in a large Mexican adult sample. The findings demonstrated several important patterns. First, emotional distress variables—particularly anxiety, stress, and depression—were strongly associated with somatic symptoms. Second, the personality trait of neuroticism emerged as a key psychological vulnerability factor, demonstrating robust correlations with both emotional distress and somatic complaints. Third, the XGBoost model showed the strongest predictive performance, explaining 42% of the variance in somatic symptoms, and SHAP analyses revealed that anxiety and neuroticism were the most influential predictors. These results indicate that somatic symptoms are not the product of isolated emotional or personality processes but rather emerge through dynamic interactions between stable psychological traits and momentary emotional states. The integration of explainable machine learning provided a transparent analytical framework to identify the most influential predictors and clarify their relative contributions to somatic symptom expression.

These findings are consistent with a large body of psychosomatic research indicating that emotional dysregulation and negative affect are central drivers of somatic symptom reporting. Previous studies have shown that emotional distress contributes to increased

physiological arousal and heightened monitoring of bodily sensations, mechanisms that can amplify the perception of physical discomfort and distress. For example, Petzke and Witthöft demonstrated that difficulties in emotion regulation significantly increase somatic symptom severity, reinforcing the finding that emotional dysregulation plays a critical role in the experience of physical symptoms (Petzke & Witthöft, 2024). The strong predictive role of anxiety identified in the present study also aligns with evidence from Kang and colleagues, who found that deficits in emotional awareness and heightened emotional arousal are associated with increased somatic symptom reporting in both community and clinical populations (Kang et al., 2025). These converging lines of evidence highlight the need to consider emotional functioning as a major mechanism underlying somatic symptom development.

The significant contribution of neuroticism observed in the machine learning models further supports previous findings that personality traits shape psychosomatic outcomes. Neuroticism is characterized by heightened emotional instability, increased worry, and sensitivity to perceived threats—including internal bodily sensations. Individuals high in neuroticism often interpret benign bodily signals as threatening or indicative of illness, which can lead to greater somatic symptom reporting. This pattern is well-established in psychosomatic research. Allemand and colleagues demonstrated that negative emotional reactivity during adolescence predicts somatic symptoms and poorer health outcomes across the lifespan (Allemand et al., 2024). Similarly, Yang's findings indicate that individuals with heightened emotional sensitivity and lower emotional differentiation tend to experience stronger associations between stressors and somatic symptoms (Yang, 2023). In the present study, the importance of neuroticism in predicting somatic symptoms using SHAP values aligns with these earlier findings and suggests that personality-linked emotional reactivity forms a stable foundation upon which emotional distress processes operate.

Beyond personality and emotional symptoms, difficulties in cognitive and emotional regulation emerged as critical mechanisms explaining somatic symptom severity. Although the present study did not directly assess emotion regulation strategies, the strong contributions of emotional variables such as anxiety and stress indirectly point to difficulties in managing emotional arousal. Previous studies provide strong support for this interpretation. For instance, Erbilidim and Nweke found that difficulties in emotion regulation mediate the relationship between guilt- and

shame-proneness and somatic symptoms, demonstrating that individuals with poor emotional regulation abilities experience heightened psychosomatic responses (Erbildim & Nweke, 2025). Likewise, Farahi and colleagues showed that maladaptive cognitive emotion regulation strategies mediate the relationship between early psychological vulnerabilities and somatic symptoms (Farahi et al., 2023). These findings align with the present results and reinforce the idea that emotional dysregulation plays a central role in psychosomatic expression.

Emotional awareness deficits also provide an important explanatory framework for understanding the identified relationships. Individuals who struggle to identify or differentiate emotions may interpret emotional arousal as physical illness, thereby increasing somatic symptom reporting. The strong predictive role of anxiety in the machine learning model supports this interpretation. Research by Lee and colleagues has shown that individuals with somatic symptom disorder exhibit changes in interoceptive accuracy and increased emotional interference, suggesting that impaired integration of emotional and bodily information contributes to somatic symptom severity (Lee et al., 2024). Orzechowska and colleagues similarly highlighted that emotional control patterns are significantly altered across somatic and psychiatric conditions, reinforcing the centrality of emotional functioning in somatic symptom expression (Orzechowska et al., 2023). These patterns collectively support the interpretation that emotional distress variables—especially anxiety—are key drivers of somatic complaints.

The SHAP results from the XGBoost model also revealed that stress and depression were significant contributors to somatic symptom severity. This is consistent with a substantial literature documenting the psychosomatic effects of chronic stress and depressive symptoms. Long-term stress exposure alters neurobiological and immunological systems, contributing to physiological disruptions and increased susceptibility to physical symptoms. Majlessi Koupaei and Farista described how emotional processes and stress can alter immune function and contribute to health problems, offering a physiological explanation for the observed associations (Majlessi Koupaei & Farista, 2024). Saadati and colleagues further showed that early trauma—which often manifests in altered stress regulation systems—has lasting psychosomatic effects in adulthood (Saadati et al., 2024). The strong role of stress observed in the present study thus falls squarely within these well-established relationships.

The findings of the present study are also consistent with clinical and qualitative research demonstrating that psychosomatic disorders often involve difficulties with emotional processing and coping. Bulut and colleagues reported that adolescents with psychosomatic disorders experience significant emotional challenges and adopt a range of coping strategies that affect their symptom patterns (Bulut et al., 2024). Similarly, Ghanavati showed that therapeutic approaches aimed at improving emotional tolerance and attachment functioning lead to reductions in psychosomatic symptoms (Ghanavati, 2024). These clinical observations complement the quantitative results of the present study by illustrating how emotional mechanisms are experienced and addressed in therapeutic contexts.

Further supporting this psychological interpretation, several studies indicate that interventions targeting emotional processes can significantly reduce psychosomatic pain and discomfort. Efremov demonstrated that emotional interventions focused on reducing negative affect can alleviate psychosomatic pain, suggesting that emotional dysregulation is not only associated with somatic symptoms but can also be effectively targeted in treatment (Efremov, 2023). Babakhanlou's structural model of emotional eating further highlights how emotional processing mechanisms mediate psychological pathways leading to maladaptive behaviors, reinforcing the central role of emotional processing in shaping behavioral and physical outcomes (Babakhanlou, 2023). Mohammadi Begi's findings that emotional variables such as depression, anxiety, and stress mediate the relationship between early trauma and somatic symptoms also align with the present study's evidence that emotional distress plays a central mediating role (Mohammadi Begi, 2023).

Taken together, the findings of this study contribute to a growing understanding of how personality traits, emotional mechanisms, and somatic symptoms interact within a complex psychosomatic system. The use of explainable machine learning offers several advantages over traditional statistical methods by enabling the detection of nonlinear patterns and clarifying the relative importance of predictors. The finding that anxiety and neuroticism were the strongest predictors aligns with earlier conceptual models of psychosomatic functioning and provides further empirical support for the central role of emotional instability in somatic symptomatology. Moreover, the integration of SHAP values adds transparency to the machine learning process, allowing the results to be interpreted in line with

existing theoretical frameworks and empirical findings across the psychosomatic literature.

Despite the strengths of a large sample size, validated measures, and the use of explainable machine learning, several limitations should be noted. First, the study employed a cross-sectional design, which limits causal inferences. The relationships among personality traits, emotional states, and somatic symptoms may be bidirectional, and longitudinal studies are needed to clarify temporal pathways. Second, data were collected through self-report questionnaires, which may introduce reporting biases such as social desirability, mood-congruent recall, or misinterpretation of items. Third, although machine learning enhances predictive accuracy, it remains constrained by the variables included; unmeasured factors such as health status, medical conditions, or environmental stressors may also contribute to somatic symptoms. Finally, the sample, although diverse within Mexico, may not generalize to populations from other cultural or socioeconomic contexts.

Future studies should employ longitudinal designs to examine how personality traits and emotional states interact over time to influence somatic symptom trajectories. Incorporating biological markers such as cortisol levels, autonomic nervous system indicators, or inflammatory biomarkers could enhance understanding of the physiological mechanisms linking emotional distress to somatic symptoms. Including objective behavioral or psychophysiological measures of emotion regulation and interoception may also reduce reliance on self-report and provide a more comprehensive view of emotional functioning. Additionally, cross-cultural research would help identify potential cultural variations in emotional processes, personality expression, and somatic symptom interpretation. Finally, future research should explore whether explainable machine learning models can be integrated into clinical assessment tools to improve screening and early intervention for individuals at risk of high somatic symptom burden.

In clinical practice, the present findings highlight the importance of assessing emotional distress, especially anxiety and stress, when treating individuals with somatic symptoms. Interventions that enhance emotional awareness, improve emotion regulation skills, and reduce maladaptive cognitive patterns may help alleviate physical complaints. Clinicians should consider personality traits, particularly neuroticism, as indicators of vulnerability that may require targeted therapeutic strategies. Integrating psychoeducation about the interaction between stress, emotions, and physical

symptoms may empower patients to understand their experiences more holistically. Additionally, incorporating explainable machine learning tools into clinical settings could support personalized assessment and identify the most relevant psychological factors contributing to each patient's symptom profile.

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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