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Modeling the Psychosocial Determinants of Problematic Social Media Use Risk Among High School Students Using Artificial Neural Networks

Özge ÇEVİK

pskdanisman99@gmail.com

Mìllì Eğìtìm Bakanliği

Cihad ŞENTÜRK

Karamanoğlu Mehmetbey University

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Abstract

Background

Problematic social media use during adolescence is shaped by interacting psychological and behavioral factors. However, evidence regarding the relative predictive contributions of these factors remains limited. This study aimed to examine academic expectation stress, loneliness, mobile device ownership, and physical activity level as predictors of Bergen Social Media Addiction Scale (BSMAS)-based risk status among high school students. To this end, an artificial neural network (ANN) model was employed, complemented by binary logistic regression analysis.

Methods

Data from 899 high school students were analyzed. Participants who scored 19 or higher on the Bergen Social Media Addiction Scale (BSMAS) were classified as being at risk for problematic social media use. A multilayer perceptron artificial neural network (ANN) model, comprising four standardized input variables, a single hidden layer with three neurons, and two output units, was trained using an internal training–test split of the dataset. Model performance was evaluated using accuracy, sensitivity, specificity, precision, F1 score, balanced accuracy, and the area under the receiver operating characteristic curve (AUC). Binary logistic regression analysis was additionally used as a complementary model to enhance interpretability.

Results

The ANN model achieved an accuracy of 93.06% in the training subset and 93.54% in the test subset. In the test subset, sensitivity was 92.80%, specificity was 96.55%, precision was 99.10%, the F1 score was 95.84%, balanced accuracy was 94.67%, and the AUC was .971. Academic expectation stress had the highest normalized importance (100.0%), followed by loneliness (58.7%), mobile device ownership (51.9%), and physical activity level (35.9%). The logistic regression model was statistically significant, $\chi^2(4) = 672.06$, $p < .001$, with a Nagelkerke R^2 of .808 and an apparent AUC of .971 (95% CI [.956, .986]). Variable ranking based on the Wald statistic reproduced the importance ranking obtained from the ANN model.

Conclusion

Academic expectation stress emerged as the most prominent predictor of risk for problematic social media use, while loneliness, mobile device ownership, and physical activity level provided complementary predictive information to the model. The convergence of the ANN and logistic regression findings supports a multidimensional understanding of risk status among adolescents. However,

external validation studies and longitudinal research designs are needed before the model can be used for individual-level screening or decision-making.

Introduction

Digital technologies have fundamentally transformed the ways in which individuals communicate, learn, access information, and spend their leisure time (Wang, 2018). Smartphones, social media platforms, online games, and digital learning environments have become an integral part of daily life, particularly among adolescents (Aschbrenner et al., 2019). Although these technologies provide important opportunities for education, communication, and entertainment, excessive and uncontrolled use has been associated with adverse academic, social, and psychological outcomes.

In this context, problematic social media use is conceptualized as a maladaptive pattern of social media engagement characterized by difficulties in controlling use, prioritizing social media over other areas of life, and consequent impairments in academic, social, or psychological functioning (Bányai et al., 2017). This pattern has been associated with core components of addictive behavior, including the increasing salience of social media use in an individual's life, escalation of use over time, use for mood regulation, withdrawal-like experiences when use is reduced, diminished control over use, and conflicts arising in personal, social, or academic domains as a result of social media use (Almog et al., 2026).

Therefore, focusing solely on screen time is insufficient when evaluating problematic social media use. Instead, the nature of social media use, individuals' self-regulation over their use, and the functional consequences of social media use in daily life should be considered together (Sindhu & Narendra, 2026). Indeed, time spent on social media alone does not necessarily indicate problematic use or addiction, as similar levels of use may have different consequences across individuals. Accordingly, assessments should take into account multiple domains of functioning, including students' academic functioning, family relationships, peer and social interactions, psychological well-being, and their ability to fulfill daily responsibilities (Reyes et al., 2022). In particular, meta-analytic evidence showing that problematic social media use is associated with symptoms of depression, anxiety, and stress suggests that the issue cannot be adequately understood solely in terms of the amount of time spent using technology (Shannon et al., 2022).

Problematic social media use should also not be regarded as a behavioral pattern that can be explained solely by individual characteristics. Recent research indicates that both individual and environmental factors, including parenting practices, family functioning, parent–adolescent relationships, peer relationships, social comparison, fear of missing out (FoMO), self-regulation skills, and psychological status, may be associated with the development of problematic social media use (Pazdur et al., 2025). Recent systematic reviews on problematic social media use among adolescents similarly indicate that positive parent–child relationships, a supportive family climate, and supportive parenting practices are associated with lower levels of problematic social media use, whereas dysfunctional family relationships, low family support, and certain negative parenting patterns may constitute risk factors

(Vossen et al., 2024). Likewise, difficulties in peer relationships, social comparison, FoMO, and negative peer pressure have been identified as potential risk factors associated with problematic social media use among adolescents (Odgers & Jensen, 2020). Taken together, these findings highlight the need to conceptualize problematic social media use within a multilevel framework encompassing the individual, family, peer, and school contexts. Accordingly, evaluations aimed at understanding students' social media use should focus not only on individual patterns of use but also on the broader social and psychosocial context in which these behaviors occur.

Adolescence is a critical developmental period characterized by substantial biological, cognitive, and psychosocial changes and is also considered an important period of vulnerability to digital addiction (Stavropoulos et al., 2015). During this stage, high school students face a range of developmental challenges, including expectations related to academic achievement, test anxiety, uncertainty about future plans, and the need for social acceptance (Latifian et al., 2024). In this context, digital environments may provide temporary emotional relief and an opportunity to disengage from everyday stressors. However, the persistent use of digital technologies as a coping mechanism may gradually develop into problematic and compulsive patterns of use. Accordingly, understanding digital addiction requires a holistic approach that considers adolescents' technology-use habits together with their psychosocial characteristics (Albayrak et al., 2026; Márquez et al., 2025). Within this broader framework, it is particularly important to examine the psychosocial and behavioral factors involved in the development of problematic social media use as a specific manifestation of digital addiction.

Problematic social media use is considered a specific form of problematic digital use and has been conceptualized in relation to features of behavioral addiction (Tereshchenko, 2023). Among the psychosocial variables associated with problematic social media use, academic stress, loneliness, and level of physical activity have received particular attention (Chen et al., 2025; Feng et al., 2026; Li et al., 2025b). Academic stressors such as expectations for academic achievement, examinations, heavy coursework, and fear of failure may lead students to turn to social media as a means of coping with negative emotions and obtaining temporary relief, and such use may gradually develop into a problematic pattern (Karaoğlan-Yılmaz et al., 2025; Ma et al., 2026; Pérez et al., 2026). Indeed, significant associations have been reported between academic stress and problematic social media use, with self-control identified as a potential mediator and social support as a potential moderator of this relationship (Ma et al., 2026; Ning & Inan, 2023). Similarly, studies conducted with secondary school students have shown that academic stress is associated with problematic social media use and that coping resources may play a protective role (Bekiroğulları & Huestis, 2026; Lie et al., 2024; Zhou & Cheng, 2026).

Loneliness is another psychosocial variable closely associated with problematic social media use. Individuals experiencing loneliness may use social media to meet needs for social connection, belonging, and interpersonal interaction. However, problematic social media use may also contribute to the displacement of face-to-face relationships by online interactions and, in turn, reinforce feelings of loneliness. Indeed, a meta-analysis of 59 studies including 81,344 participants found a moderate positive association between problematic social media use and loneliness, whereas the association

between time spent on social media and loneliness was small (Feng et al., 2026). This finding suggests that, when evaluating problematic social media use, greater emphasis should be placed on the problematic nature of use rather than on duration of use alone.

Physical activity, including both participation in and overall level of activity, is also considered an important behavioral factor associated with problematic social media use. Longitudinal studies have shown that problematic social media use at baseline predicts subsequent decreases in physical activity, whereas the intensity of social media use alone does not emerge as a significant predictor (Koning et al., 2026). Physical activity has also been suggested to serve as a protective factor that may mitigate the psychological consequences of problematic social media use, particularly by moderating the association between problematic use and anxiety symptoms (Niemistö et al., 2026). Taken together, these findings suggest that problematic social media use should be evaluated not solely in terms of time spent on social media, but in conjunction with psychosocial and behavioral factors such as academic stress, loneliness, and physical activity.

Research on problematic social media use has extensively employed conventional statistical approaches, including correlation analysis, multiple regression, hierarchical regression, and structural equation modeling. These methods provide important tools for identifying relationships among variables, examining the relative contributions of predictors, and testing mediation and moderation effects (Aljomaa et al., 2016; Inga-Ávila et al., 2025; Temur et al., 2026). For example, a large-sample study of adolescents used hierarchical regression to examine the contributions of demographic characteristics, social support, well-being, and media-use-related variables to problematic social media use (van Duin et al., 2021).

However, the fact that problematic social media use is shaped by the interplay of individual, psychological, social, and behavioral variables indicates a need for more flexible analytical approaches in addition to linear models. Students experiencing similar levels of academic stress may exhibit different levels of problematic use because of differences in loneliness, social support, self-control, physical activity, and patterns of social media use, illustrating the complexity of this phenomenon. In this context, machine learning methods capable of identifying nonlinear relationships and complex variable patterns offer a complementary alternative to conventional statistical approaches. Indeed, Savcı et al. (2022) used artificial neural networks and support vector machines to predict problematic social media use by jointly examining FoMO, online socialization, desire for social approval, and personality traits. More recent studies have examined nonlinear relationships between problematic social media use and psychological well-being using XGBoost and SHAP methods (Tian, 2026), while longitudinal research has shown that baseline problematic social media use, anxiety, and coping styles can predict problematic use at subsequent time points (Zarate et al., 2026). Overall, incorporating machine learning approaches capable of identifying complex and nonlinear patterns among multiple variables, alongside conventional statistical methods, may provide an important methodological contribution to the literature on problematic social media use.

Recent advances in artificial intelligence and machine learning have introduced promising alternative methods for examining behavioral health outcomes (Qiao & Li, 2026). Among these methods, artificial neural networks (ANNs) are particularly notable for their ability to model nonlinear relationships in multidimensional datasets and their potential to predict individual risk profiles with high accuracy. Unlike conventional statistical methods, ANN models can capture latent interactions among variables and model complex behavioral patterns without requiring an assumption of linear relationships (Ahmed, 2005; Ayer et al., 2010). In this way, they may not only improve predictive accuracy but also facilitate the identification of psychosocial variables that make the greatest contribution to the risk of problematic social media use. Owing to these characteristics, artificial neural networks have considerable potential for the development of data-driven early risk identification systems and evidence-based intervention strategies (Karaman, 2025; Wahed & Wahed, 2025).

In the present study, the risk of problematic social media use among high school students was modeled using artificial neural networks, focusing on three key psychosocial and behavioral determinants: academic expectation stress, loneliness, and physical activity level. Rather than relying solely on the frequency of technology use, the study adopts a holistic approach by examining the joint contribution of psychosocial and behavioral characteristics to the risk of problematic social media use. By employing an artificial intelligence-based predictive model, this study is expected to address an important gap in the literature concerning the nonlinear relationships underlying problematic social media use among adolescents. The findings are expected to contribute to the early identification of students at risk, support the development of school-based psychological counseling and preventive mental health practices, and provide empirical evidence for designing effective intervention programs aimed at promoting healthy and balanced social media use among adolescents.

Conceptual Framework

Problematic Social Media Use as a Behavioral Addiction

Social media addiction is conceptualized as a problematic pattern of behavior characterized by difficulty controlling social media use, prioritizing social media over other areas of life, and continuing use despite adverse consequences (Liang et al., 2024). Although social media addiction is not recognized as an independent clinical diagnosis in the DSM-5 or ICD-11, it is commonly examined within the broader framework of behavioral addictions (Montag et al., 2024; Tereshchenko, 2023; WHO [World Health Organization], 2019; Zhou et al., 2024). Therefore, the assessment of social media use should focus not only on duration of use, but also on loss of control, increasing priority given to use, and impairments in academic, social, and psychological functioning.

Problematic social media use is a multidimensional process that emerges from the interplay of individual and psychosocial factors (Amirthalingam & Khera, 2024). Difficulties in self-control, impulsivity, emotion regulation problems, loneliness, and the need for social acceptance have all been reported to be associated with problematic social media use (Montag et al., 2024). This issue is

particularly relevant during adolescence. As peer acceptance, social belonging, and identity development become increasingly salient during this developmental period, social feedback received through social media platforms may become especially reinforcing. At the same time, research on the psychological and neurobiological effects of social media use is still evolving, and definitive claims that social media use directly produces a specific neurobiological mechanism of addiction should therefore be avoided (Hannapel & Aghajani, 2025).

The psychosocial consequences of problematic social media use are also important for understanding its behavioral addiction-like characteristics. Research has shown that problematic social media use may be associated with a range of psychosocial outcomes, including depressive symptoms, anxiety, loneliness, lower psychological well-being, impaired social functioning, and sleep problems (Arness & Ollis, 2022; Kıran et al., 2020; Shannon et al., 2022). In particular, when social media use adversely affects individuals' academic responsibilities, family relationships, peer relationships, and daily life activities, this indicates that the behavior extends beyond merely "intensive use" and should instead be evaluated in terms of its functional consequences (Bányai et al., 2017).

Overall, problematic social media use should be considered within a behavioral addiction framework that emphasizes the quality of social media use, loss of control, and functional consequences rather than the quantity of use alone. Within this framework, key indicators of problematic social media use include the increasing priority of social media use in an individual's life, using social media for mood regulation, diminished control over use, negative experiences when use is reduced, interpersonal or intrapersonal conflicts related to use, and a tendency to resume use after attempts to stop (Andreassen et al., 2012; Hylkilä et al., 2025). At the same time, given that problematic social media use is not currently recognized as an independent diagnosis in the DSM-5 or ICD-11, it should be acknowledged that the term "addiction" in the literature is generally used within the conceptual framework of behavioral addiction and problematic social media use.

Academic Expectation Stress and Problematic Social Media Use

Academic expectation stress refers to the psychological pressure students experience in attempting to meet their own expectations for academic achievement as well as the expectations they perceive from their families, teachers, and school environment (Ang & Huan, 2006; Bedewy & Gabriel, 2015). This form of stress may arise from fear of academic failure, examinations, heavy academic workload, and high achievement expectations, and may negatively affect students' psychological well-being. When academic expectations exceed an individual's coping resources, students may turn to social media as a way of coping with stress and negative emotions. In such cases, social media use may function as a short-term source of relief and escape and may gradually contribute to the development of a problematic pattern of use (Babiker et al., 2023; Cui et al., 2023). Indeed, a recent meta-analysis including 166 effect sizes from 49 studies and a total of 189,483 adolescents reported a positive association between academic stress and problematic internet use (Chen et al., 2025).

Direct empirical studies examining the relationship between academic expectation stress and problematic social media use also support this association. For example, a 2026 study conducted with secondary school students found that academic stress was a significant predictor of problematic social media use; stress symptoms were positively associated with problematic social media use, whereas coping resources were negatively associated with it (Pérez et al., 2026). Similarly, a recent study involving university students showed that academic pressure directly increased problematic social media use, self-control mediated this relationship, and social support weakened the association between academic pressure and problematic social media use (Ma et al., 2026).

This relationship may be explained through stress-coping and emotion-regulation processes. Students experiencing intense academic pressure may use social media as a form of escape or a short-term emotion-regulation strategy to reduce fear of failure and psychological distress. However, when this pattern of use becomes persistent, it may make social media use more difficult to control (Shiraly et al., 2024). Indeed, a study conducted with doctoral students found that anxiety and desire thinking sequentially mediated the relationship between academic stress and problematic social media use, while loneliness strengthened this association (He & Zhu, 2024). Likewise, longitudinal research with adolescents has shown that psychological distress may mediate the relationship between academic stress and addictive tendencies (Yang et al., 2023).

Accordingly, the relationship between academic expectation stress and problematic social media use should not be viewed as a simple or unidirectional process. Although academic pressure may increase students' tendency to turn to social media, problematic social media use may also adversely affect academic adjustment through processes such as disengagement from academic responsibilities, attentional difficulties, and academic procrastination (Huang et al., 2025). Therefore, academic expectation stress can be considered an important psychosocial risk factor in explaining problematic social media use (Sudha & Sharma, 2025). However, variables such as self-control, social support, loneliness, and psychological distress should also be taken into account when interpreting this relationship. Current evidence suggests that considering problematic social media use together with academic stress may provide a more holistic understanding of students' psychological and academic adjustment (Pérez et al., 2026).

Loneliness and Problematic Social Media Use

Loneliness is defined as a subjective and negative experience arising from a perceived discrepancy between an individual's existing social relationships and the relationships they desire (Perlman & Peplau, 1981). Rather than simply reflecting the state of being physically alone, loneliness refers to a subjective sense of social disconnection resulting from insufficient perceived intimacy and connectedness within existing relationships (Wu et al., 2024). During adolescence in particular, the increasing importance of peer acceptance, belonging, and social support makes loneliness an important psychosocial factor in relation to problematic social media use (Qualter et al., 2015). The literature suggests that feelings of loneliness may be reinforced by the temporary relief provided through social interactions on social

media, which may increase the desire to fill an emotional void and, in turn, elevate the risk of problematic use (Erdemir & Ayas, 2023; Temur et al., 2026).

According to the social compensation perspective, individuals who are dissatisfied with their face-to-face social relationships may turn to online environments to meet unmet needs for belonging and acceptance (McKenna & Bargh, 2000). Accordingly, adolescents may use social media, online games, and other digital platforms as alternative spaces for socialization in order to alleviate feelings of loneliness (Güner et al., 2022). Recent research also indicates a significant association between loneliness and problematic social media use. Indeed, a 2026 meta-analysis including 59 studies and 81,344 participants found a moderate positive association between problematic social media use and loneliness, whereas the association between time spent on social media alone and loneliness was very small (Feng et al., 2026). The social compensation perspective provides an important theoretical framework for explaining this relationship. From this perspective, individuals who do not obtain sufficient satisfaction from face-to-face relationships may seek to meet unmet needs for social connection and belonging in online environments (Ellison et al., 2007). Individuals experiencing loneliness, in particular, may use social media platforms to establish social interactions and seek social support (O'Day & Heimberg, 2021). However, online interactions do not always provide the social support sought, and problematic patterns of use may subsequently emerge (Chao et al., 2025).

The relationship between loneliness and problematic social media use is not explained solely by a greater tendency to engage with online environments; it is also conceptualized as a mutually reinforcing process in which problematic use and loneliness may intensify one another (Wu et al., 2024). While individuals experiencing loneliness may obtain a temporary sense of social connection and belonging through social media, excessive and increasingly difficult-to-control use may be associated with reduced face-to-face interaction (Büyükgebiz-Koca & Tunca, 2019). This, in turn, may contribute to a cycle in which loneliness increases and individuals subsequently turn back to social media. Meta-analytic reviews of longitudinal studies also suggest that loneliness and problematic media use may be reciprocally related (Fam & Männikkö, 2025). The quality of social relationships also plays an important role in this process during adolescence. Poor peer relationships, social exclusion, negative peer experiences, and social comparison have been associated with the development of problematic social media use (Al-Samarraie et al., 2021; Pazdur et al., 2025). Accordingly, loneliness should not be regarded as an isolated cause of problematic social media use, but rather as a risk factor that needs to be considered in interaction with the individual's social environment, psychological characteristics, and patterns of social media use.

Overall, the relationship between loneliness and problematic social media use should not be interpreted as a unidirectional cause-and-effect relationship. Current evidence suggests that loneliness may increase vulnerability to problematic social media use, while problematic social media use may also be associated with greater loneliness. Within this reciprocal relationship, social approval and visibility obtained through online environments may provide short-term psychological gratification; however, when online interactions begin to replace face-to-face social relationships, individuals may invest less in their

offline relationships, potentially contributing to the persistence of loneliness (Nowland et al., 2018). Therefore, the assessment of problematic social media use should focus not only on duration of use, but also on whether social media is used to meet social needs, the extent of loss of control over use, and its impact on individuals' face-to-face social relationships (Feng et al., 2026; O'Day & Heimberg, 2021).

Physical Activity and Problematic Social Media Use

Physical activity is defined as any bodily movement produced by skeletal muscles that requires energy expenditure (WHO [World Health Organization], 2020). Regular physical activity contributes not only to physical health but also to psychological well-being, cognitive functioning, and social development. Maintaining regular physical activity is particularly important during childhood and adolescence for the development of healthy lifestyle habits. The World Health Organization recommends that children and adolescents aged 5–17 years engage in an average of at least 60 minutes per day of moderate-to-vigorous physical activity across the week (WHO, 2020). During adolescence in particular, regular physical activity may play a protective role against the risk of digital addiction by reducing stress, supporting emotion regulation, strengthening self-control, and promoting social interaction (Biddle & Asare, 2011; Lubans et al., 2016).

In contrast, low levels of physical activity may reinforce a sedentary lifestyle and lead individuals to spend a greater proportion of their leisure time in digital environments (Gülü et al., 2023; Ren et al., 2022). The relationship between physical activity and social media use has received increasing research attention, particularly among adolescents (Goodyear et al., 2021; Morningstar et al., 2023; Shimoga et al., 2019). Several studies have shown that adolescents with problematic social media use may have lower levels of physical activity. For example, a large-scale study involving 96,919 adolescents found that students at risk of problematic social media use had lower levels of physical activity (Ardesch et al., 2023).

However, the relationship between social media use and physical activity cannot be explained solely by time spent on social media. Indeed, a comprehensive systematic review and meta-analysis reported no significant association between social media use duration and adolescents' physical activity levels (Purba et al., 2023). Therefore, it is important to examine the relationship between physical activity and problematic social media use in terms of the problematic nature of use rather than duration alone. In a two-wave longitudinal study of adolescents, Koning et al. (2026) found that baseline problematic social media use was associated with changes in physical activity one year later, whereas social media use intensity alone did not show the same explanatory value. This finding further supports the need to consider loss of control and other features of problematic use, rather than duration of social media use alone, when examining behavioral outcomes.

Physical activity may also be an important factor in relation to the psychological consequences of problematic social media use. A recent study examining the associations of problematic social media use with symptoms of depression and anxiety found that moderate-to-vigorous physical activity could

attenuate the adverse association between problematic social media use and anxiety symptoms, particularly among adolescent girls (Niemistö et al., 2026). This finding suggests that physical activity should be considered not only as a behavior that may reduce social media use, but also as a lifestyle factor that may be associated with the psychological consequences of problematic use.

Overall, the relationship between physical activity and problematic social media use should not be interpreted as a unidirectional cause-and-effect relationship. Existing evidence suggests that low physical activity may be associated with problematic social media use and that problematic use may also be related to subsequent changes in physical activity levels (Ardesch et al., 2023; Koning et al., 2026). Therefore, assessments of problematic social media use should consider not only the duration of social media use, but also individuals' physical activity level, sedentary behavior, and broader lifestyle patterns.

Research Aim

The primary aim of this study is to determine the relative importance of academic expectation stress, loneliness, mobile device ownership, and physical activity in classifying problematic social media use status among high school students. The contributions of these variables to the prediction of problematic social media use are examined comparatively within the same artificial neural network model. In this respect, the study seeks to empirically test contemporary theoretical perspectives suggesting that problematic social media use cannot be reduced solely to technology use and should instead be understood through the combined consideration of individuals' psychosocial processes and lifestyle characteristics.

A further distinctive aim of the study is to establish the relative importance ranking of the determinants of problematic social media use and to identify which variables play a more dominant role in the emergence of risk. While much of the existing literature has focused on linear relationships among variables, the present study evaluates the relative contributions of psychosocial and behavioral factors to problematic social media use within a single integrated model. In doing so, the study aims to contribute to a more comprehensive understanding of the multidimensional nature of problematic social media use.

Artificial neural networks (ANNs) were employed to model the complex and nonlinear relationships among these variables. Unlike conventional statistical methods, ANNs can model interactions among variables with high predictive accuracy and estimate the relative importance of variables associated with problematic social media use. In this context, the study is expected to provide empirical evidence not only for understanding the psychosocial mechanisms underlying problematic social media use, but also for the early identification of students at risk, the development of school-based preventive intervention programs, and the prioritization of resources toward the most influential risk factors. In this way, the study aims to make both theoretical and methodological contributions to the literature on problematic social media use. Accordingly, the following research questions were addressed:

1. Which of the following variables—academic expectation stress, loneliness, mobile device ownership, and physical activity—has the highest relative importance in classifying problematic social media use status among high school students?
2. When academic expectation stress, loneliness, mobile device ownership, and physical activity are considered simultaneously, with what level of accuracy and discriminative performance does the multilayer perceptron artificial neural network (MLP-ANN) model classify problematic social media use status?
3. What theoretical and practical implications does the variable importance ranking obtained from the ANN model provide for understanding the risk of problematic social media use among high school students and for prioritizing school-based preventive interventions?

Methods

Research Design

This study adopted a quantitative research approach to determine the relative importance of psychosocial and behavioral variables in predicting problematic social media use among high school students, and the data were analyzed using an artificial neural network (ANN) model. Problematic social media use constituted the dependent variable, whereas academic expectation stress, loneliness, mobile device ownership, and physical activity were included as input variables. A multilayer perceptron (MLP) architecture was used to examine nonlinear relationships among the variables and to determine the relative importance of the predictors in classifying problematic social media use.

The ANN model served as the primary predictive approach. In addition, a binary logistic regression model using the same binary outcome variable and the same four predictors was employed as a complementary analysis to compare the findings with those obtained from a more interpretable parametric method.

Study Group

The study group consisted of 900 students enrolled in different types of high schools in the city center of Karaman, Türkiye, during the 2025–2026 academic year. Participants were included in the study on a voluntary basis, with a maximum variation approach used to ensure representation across different school types and grade levels. One participant with missing data on any of the variables used in the artificial neural network analysis was excluded, and the final analyses were conducted with 899 students. Prior to data collection, the required ethics committee approval and institutional permissions were obtained. Students and their parents were informed about the study, and the relevant voluntary participation and consent procedures were completed for both students and parents.

Data Collection Instruments

Several measurement instruments were used to assess psychosocial and behavioral variables associated with problematic social media use among the students. Specifically, scales were administered to measure academic expectation stress, perceived loneliness, physical activity level, and problematic social media use. The data collection instruments used in the study are briefly described below.

Academic Expectations Stress Inventory

The Academic Expectations Stress Inventory was used to assess students' levels of stress associated with academic expectations. The inventory was originally developed by Ang and Huan (2006) to evaluate stress arising from academic achievement expectations, test anxiety, and expectations for achievement perceived from family members and the broader social environment, and was adapted into Turkish for high school students by Kelecioğlu and Bilge (2009). The Likert-type instrument consists of nine items across two subdimensions: family/teacher expectations and self-expectations. In the Turkish adaptation study, internal consistency coefficients ranged from .65 to .82, and the instrument was found to be a valid and reliable measure of academic expectation stress among high school students. In the present study, scores obtained from the inventory were used to represent students' levels of academic expectation stress, and this variable was examined in relation to problematic social media use.

UCLA Loneliness Scale – Short Form

The short form of the UCLA Loneliness Scale was used to assess students' levels of loneliness. The scale was derived by Hays and DiMatteo (1987) from the original 20-item UCLA Loneliness Scale developed by Russell et al. (1978) to assess perceived loneliness and feelings of social isolation in interpersonal relationships. The Likert-type short form consists of eight items designed to measure perceived loneliness, with higher scores indicating higher levels of loneliness. The Turkish adaptation and validity and reliability study of the scale was conducted by Doğan et al. (2011). Factor analysis indicated a single-factor structure accounting for 36.69% of the total variance. The internal consistency coefficient was reported as Cronbach's $\alpha = .72$, and the scale was found to be a valid and reliable instrument for assessing loneliness among high school students. In the present study, scale scores were used to represent students' levels of loneliness, and loneliness was examined as a predictor of problematic social media use.

International Physical Activity Questionnaire – Short Form

The International Physical Activity Questionnaire–Short Form (IPAQ-SF) was used to assess students' physical activity levels. The IPAQ was developed by Craig et al. (2003) to provide an internationally comparable assessment of physical activity. The short form includes questions on walking, moderate-intensity physical activity, vigorous-intensity physical activity, and daily sitting time during the previous

seven days. Participants were asked to report how many days per week they engaged in each activity and how much time they spent on these activities per day. Based on these responses, total physical activity was calculated in MET-minutes/week, and participants were classified as having low, moderate, or high physical activity levels. The Turkish adaptation and validity and reliability study of the questionnaire was conducted by Öztürk (2005), and the instrument was found to be valid and reliable for assessing physical activity in Turkish samples. In the present study, data obtained from the questionnaire were used to determine students' physical activity levels, and physical activity was examined in relation to problematic social media use.

Bergen Social Media Addiction Scale

The Bergen Social Media Addiction Scale (BSMAS) was used to assess symptoms of problematic social media use. The scale was developed by Andreassen et al. (2016) to assess behavioral addiction symptoms related to social media use and was adapted into Turkish by Demirci (2019). The six-item, 5-point Likert-type scale assesses six core components of behavioral addiction: salience, mood modification, tolerance, withdrawal, conflict, and relapse. Total scores range from 6 to 30, with higher scores indicating higher levels of symptoms associated with problematic social media use. In the present study, the BSMAS score was used to derive the risk status for problematic social media use.

Definition and Binary Outcome Classification

In this study, "problematic social media use status" refers to risk for social media-related problematic use as assessed by the BSMAS. Because the BSMAS measures addiction-related symptoms specifically associated with social media use rather than all forms of digital technology use, the findings were interpreted within this measurement scope. The binary outcome variable was created based on the BSMAS total score.

In accordance with the screening threshold proposed by Bányai et al. (2017) in a large, nationally representative adolescent sample, participants with a BSMAS total score of 19 or higher were coded as being at risk for problematic social media use (Class 1), whereas those scoring below 19 were coded as not being at risk (Class 0). This threshold was used for risk screening and classification purposes rather than for establishing a clinical diagnosis.

Data Collection Procedure

Data were collected face-to-face over a one-month period during the 2025–2026 academic year. Completion of the full set of data collection instruments took approximately 30–35 minutes. Participation in the study was voluntary. Prior to data collection, participants were informed about the purpose of the study, the content and administration of the data collection instruments, the voluntary

nature of participation, and their right to withdraw from the study at any stage without penalty or adverse consequences. Participants were also assured that the information they provided would remain confidential and that no identifying information would be used at any stage of the research process.

Data Analysis and Artificial Neural Network Modeling

The data were analyzed using an artificial neural network model based on a multilayer perceptron (MLP) architecture. Analyses were conducted using the Neural Networks module in IBM SPSS Statistics 27. The MLP approach was selected because it can model potential nonlinear patterns among variables and allows the relative contribution of input variables to classification to be evaluated (Rumelhart et al., 1986). Similarly, ANN models have been used in educational classification and behavioral addiction research to examine nonlinear relationships and determine variable importance (Aryadoust & Baghaei, 2016; Chen & Zhang, 2024; Li et al., 2025a).

The dataset was randomly partitioned with an approximate target ratio of 70% for training and 30% for testing. In the resulting split, 605 observations (67.3%) were included in the training subset and 294 observations (32.7%) in the test subset. Because test error was monitored as part of the SPSS stopping rule, the test subset was treated as an internal test partition rather than as an independent external validation sample (Vabalas et al., 2019).

Artificial Neural Network Architecture and Model Structure

The final MLP model used in the study consisted of three main layers: an input layer, a single hidden layer, and an output layer. The model included four input units representing academic expectation stress, loneliness, mobile device ownership, and physical activity, and all input variables were standardized prior to analysis. The hidden layer comprised three neurons, while the output layer contained two units representing the two categories of BSMAS-based risk status. Accordingly, rather than predicting the BSMAS total score as a continuous outcome, the model was configured to classify participants as either not at risk (Class 0) or at risk (Class 1) for problematic social media use.

Activation Functions and Training Process

To facilitate the learning of nonlinear relationships, the hyperbolic tangent (tanh) activation function was used in the hidden layer, whereas the Softmax activation function was applied in the output layer because of its suitability for classification problems. Consistent with the categorical outcome structure, cross-entropy was specified as the error function. Network training was performed using the batch method with the scaled conjugate gradient optimization algorithm, which is an optimization approach designed to improve computational efficiency in supervised neural network training (Møller, 1993).

Model performance was evaluated using overall and class-specific classification accuracy, sensitivity, specificity, precision, F1 score, balanced accuracy, and the area under the receiver operating characteristic curve (AUC) (Fawcett, 2006). The relative contributions of the predictors were examined using the raw and normalized importance values generated by SPSS. Normalized importance values were interpreted as indicators of relative predictive contribution within the specified network rather than as effect sizes or causal effects (Olden et al., 2004).

Model performance was evaluated using a single random training–test split. No independent external validation sample or k-fold cross-validation procedure was used. Accordingly, the test results were interpreted as indicators of internal discriminative performance rather than external validation performance (Vabalas et al., 2019). The architecture of the final MLP-ANN model is presented in Fig. 1.

Note

The model consisted of four standardized input variables, one hidden layer with three neurons, and two output units. The hidden layer used the hyperbolic tangent activation function and the output layer used Softmax.

Complementary Binary Logistic Regression Analysis

To evaluate the findings obtained from the ANN model against a more interpretable parametric benchmark, a binary logistic regression analysis was conducted using the same binary outcome variable and the same four predictors. Logistic regression was treated as a complementary benchmark model because it provides probability-based predictions for binary outcomes and allows model coefficients to be interpreted in terms of odds ratios (ORs) and 95% confidence intervals (Hosmer et al., 2013). Given the different modeling properties of ANN and logistic regression, the two approaches were not treated as competing alternatives, but rather as complementary evaluations of parametric/linear and nonlinear predictive patterns (Ayer et al., 2010).

All four predictors were entered simultaneously into the model using the Enter method. Overall model significance was evaluated using the Omnibus Test of Model Coefficients, model fit was assessed using the Hosmer–Lemeshow test, and the model's relative explanatory capacity was examined using Cox–Snell and Nagelkerke pseudo-R^2 values. For each predictor, the regression coefficient (B), standard error (SE), Wald χ^2 statistic, p value, odds ratio [OR; Exp(B)], and 95% confidence interval were reported. Classification performance was calculated using a .50 cutoff, and ROC analysis was additionally conducted using the predicted probabilities saved from the model. The AUC, standard error, and 95% confidence interval were reported (Fawcett, 2006).

Because the classification and ROC indices for the logistic regression model were derived from the same analytical sample of 899 participants used to fit the model, these values were interpreted as within-sample (apparent) measures of discriminative performance rather than as estimates of external-

sample performance. Comparisons between the logistic regression and ANN models were therefore kept descriptive. Because the reported ANN performance was based on the internal test subset generated by SPSS, whereas logistic regression performance was based on the full analytical sample, no formal superiority test based on accuracy or AUC was conducted.

Results

Classification Performance of the Artificial Neural Network Model

The final MLP-ANN model demonstrated high classification performance in both the training and test subsets. In the training subset, the cross-entropy error was 104.819 and the misclassification rate was 6.94%, corresponding to an overall classification accuracy of 93.06%. In the test subset, the cross-entropy error was 48.941, the misclassification rate was 6.46%, and the overall classification accuracy was 93.54%.

The close correspondence between training and test accuracy indicates that the classification pattern learned from the training data was largely maintained in the test subset. Because the two subsets differed in sample size, absolute cross-entropy values were not compared directly; interpretation therefore focused on classification and discriminative performance metrics. The classification performance of the MLP-ANN model in the training and testing subsets is presented in Table 1.

Table 1
Classification performance of the multilayer perceptron artificial neural network

Sample	Observed class	Predicted Class 0	Predicted Class 1	Correctly classified
Training	Class 0	132	8	94.29%
Training	Class 1	34	431	92.69%
Training overall				93.06%
Testing	Class 0	56	2	96.55%
Testing	Class 1	17	219	92.80%
Testing overall				93.54%

Note. Training n = 605; testing n = 294. Class 0 = not at risk (BSMAS < 19); Class 1 = at risk for problematic social media use (BSMAS > = 19). Class 1 was treated as the positive category for the calculation of sensitivity, precision, and F1 score.

Class-level results were also consistent with the overall model performance. In the training subset, 132 of 140 observations in the not-at-risk group (Class 0) were correctly classified (94.29%), while 431 of 465 observations in the at-risk group (Class 1) were correctly classified (92.69%). In the test subset, 56 of 58

observations in Class 0 were correctly classified (96.55%), whereas 219 of 236 observations in Class 1 were correctly classified (92.80%). This distribution indicates that the high overall classification accuracy was not driven solely by correct classification of the majority class.

Class-Based Performance and ROC Analysis

When the at-risk group (Class 1) was treated as the positive class, sensitivity in the test subset was 92.80%, specificity was 96.55%, and precision was 99.10%. The F1 score, which summarizes precision and sensitivity jointly, was 95.84%, while balanced accuracy, which gives equal weight to performance in both classes, was 94.67%. These findings indicate that, despite the numerical imbalance between the two classes, the model was able to distinguish both at-risk and not-at-risk participants with high classification performance. The predictive performance metrics of the MLP-ANN model in the testing subset are summarized in Table 2.

Table 2
Predictive performance of the MLP-ANN in the testing subset

Performance metric	Value
Overall accuracy	93.54%
Sensitivity	92.80%
Specificity	96.55%
Precision	99.10%
F1 score	95.84%
Balanced accuracy	94.67%
AUC	.971

Note. Class 0 = not at risk (BSMAS < 19); Class 1 = at risk for problematic social media use (BSMAS > = 19). Class 1 was treated as the positive category. AUC = area under the receiver operating characteristic curve.

ROC analysis further supported the classification results. The AUC was .971 for both output categories. As AUC values approach 1.00, the model's ability to discriminate between classes increases (Fawcett, 2006). Accordingly, the model demonstrated very high discrimination between the BSMAS-based risk categories within the current sample. However, because the test subset was used as part of the model's stopping rule, this finding was interpreted as internal discriminative performance rather than as evidence of independent external validation. The receiver operating characteristic curves for the MLP-ANN model are presented in Fig. 2.

Note

AUC = .971 for both risk-status categories. Class 0 = not at risk (BSMAS < 19); Class 1 = at risk for problematic social media use (BSMAS > = 19). The diagonal line represents chance-level discrimination.

Relative Importance of Predictor Variables

The variable importance analysis showed that the four input variables contributed to the model's predictions to different degrees. Academic expectation stress was the strongest predictor, with a raw importance value of .406 and a normalized importance of 100.0%. Loneliness ranked second, with a raw importance of .238 and a normalized importance of 58.7%, followed by mobile device ownership, with a raw importance of .211 and a normalized importance of 51.9%. Physical activity level had the lowest relative contribution, with a raw importance of .145 and a normalized importance of 35.9%. The relative importance and normalized importance values of the predictor variables are presented in Table 3.

Table 3
Relative importance of predictor variables in the MLP-ANN model

Predictor	Importance	Normalized importance	Rank
Academic expectation stress	.406	100.0%	1
Loneliness	.238	58.7%	2
Mobile device ownership	.211	51.9%	3
Physical activity	.145	35.9%	4

Note. The predictor with the highest raw importance was scaled to 100%; the remaining predictors were expressed relative to this reference. Importance values are not regression coefficients or percentages of explained variance.

A normalized importance value of 100.0% for academic expectation stress does not indicate that this variable explains the entirety of problematic social media use status; rather, it reflects that the predictor with the highest relative importance in the network was scaled as the reference value (Olden et al., 2004). Similarly, the fourth-place ranking of physical activity does not imply that this variable made no contribution to classification. Its normalized importance value of 35.9% indicates that it provided additional predictive information to the model when considered together with the other input variables. The normalized importance values of the predictor variables are presented in Fig. 3.

Note

The predictor with the highest importance was standardized to 100%, and the normalized importance of the remaining variables was expressed relative to this reference.

Complementary Binary Logistic Regression Findings

The complementary binary logistic regression model converged after seven iterations, and estimation was terminated when the change in parameter estimates fell below .001. The model including all four predictors provided a significantly better fit than the intercept-only model, $\chi^2(4) = 672.06$, $p < .001$. The Cox–Snell pseudo-R^2 was .526 and the Nagelkerke pseudo-R^2 was .808. The Hosmer–Lemeshow test

was not statistically significant, $\chi^2(4) = 3.46$, $p = .483$, indicating no evidence of substantial discrepancy between the observed and model-expected classifications (Hosmer et al., 2013).

At a classification cutoff of .50, the model correctly classified 94.8% of cases. The correct classification rate was 85.9% (170/198) for the not-at-risk group (Class 0) and 97.3% (682/701) for the at-risk group (Class 1). All four predictors were statistically significant in the model. Academic expectation stress showed the largest Wald statistic, B = -4.604, SE = .377, Wald $\chi^2 = 148.78$, $p < .001$, OR = .010, 95% CI [.005, .021]. This was followed by loneliness, B = -2.521, SE = .334, Wald $\chi^2 = 57.05$, $p < .001$, OR = .080, 95% CI [.042, .155]; mobile device ownership, B = -3.877, SE = .897, Wald $\chi^2 = 18.69$, $p < .001$, OR = .021, 95% CI [.004, .120]; and physical activity level, B = − .903, SE = .339, Wald $\chi^2 = 7.09$, $p = .008$, OR = .405, 95% CI [.209, .788].

Because the directional interpretation of the coefficients depends on the category and reference coding of the predictors and outcome, emphasis was placed on their statistical contribution within the model and the corresponding confidence intervals rather than on directional interpretation alone. The results of the binary logistic regression analysis are presented in Table 4.

Table 4

Binary logistic regression results predicting dependency status

Predictor	**B**	**SE**	**Wald χ^2**	**p**	**OR**	**95% CI for OR**
Mobile device ownership	-3.877	.897	18.692	< .001	.021	[.004, .120]
Loneliness	-2.521	.334	57.048	< .001	.080	[.042, .155]
Academic expectation stress	-4.604	.377	148.776	< .001	.010	[.005, .021]
Physical activity	− .903	.339	7.089	.008	.405	[.209, .788]

Note. N = 899. Outcome coding: Class 0 = not at risk (BSMAS < 19); Class 1 = at risk for problematic social media use (BSMAS > = 19). B = unstandardized logistic regression coefficient; SE = standard error; OR = odds ratio; CI = confidence interval. The substantive direction of each odds ratio depends on the predictor category/reference coding used in SPSS.

ROC analysis indicated high discriminative performance for the logistic regression model: AUC = .971, SE = .007, 95% CI [.956, .986], $p < .001$. This AUC was numerically identical to the value of .971 obtained for the ANN model. However, because the logistic regression AUC was derived from predicted probabilities generated for the full analytical sample, whereas the ANN AUC was based on SPSS's internal test subset, the identical AUC values were not interpreted as evidence of formally equivalent model performance. A more appropriate interpretation is that both approaches demonstrated strong discriminative performance within the current dataset.

Notably, the descending order of the Wald statistics in the logistic regression model—academic expectation stress, loneliness, mobile device ownership, and physical activity—mirrored the normalized

importance ranking obtained from the ANN model. This cross-method consistency suggests that the prominent role of academic expectation stress was not specific to a single analytical technique. Nevertheless, because Wald statistics and ANN importance values differ in scale, statistical meaning, and purpose, they were not treated as quantitatively interchangeable measures.

Overall Evaluation of Findings

Taken together, the MLP-ANN model achieved an accuracy of 93.06% in the training subset and 93.54% in the test subset. In the test subset, sensitivity was 92.80%, specificity was 96.55%, the F1 score was 95.84%, balanced accuracy was 94.67%, and the AUC was .971. The variable importance ranking was academic expectation stress (100.0%) > loneliness (58.7%) > mobile device ownership (51.9%) > physical activity (35.9%).

The complementary binary logistic regression model was also statistically significant, $\chi^2(4) = 672.06$, $p < .001$, with a Nagelkerke pseudo-R^2 of .808 and an overall within-sample classification accuracy of 94.8%. The logistic regression model yielded an AUC of .971 (95% CI [.956, .986]), and the ordering of the Wald statistics mirrored the variable importance ranking obtained from the ANN model. These converging findings support academic expectation stress as the most prominent variable in the classification of problematic social media use status, while loneliness, mobile device ownership, and physical activity provided additional predictive information to the model.

However, because logistic regression performance was evaluated on the full analytical sample, whereas ANN performance was evaluated using the internal test subset, no direct claim of superiority between the two models was made.

Discussion

In this study, the relative contributions of academic expectation stress, loneliness, mobile device ownership, and physical activity to the classification of BSMAS-based risk for problematic social media use among high school students were examined using two complementary analytical approaches. The MLP-ANN model demonstrated high internal discriminative performance in the test subset, with an accuracy of 93.54% and an AUC of .971. Academic expectation stress showed the highest normalized importance, followed by loneliness, mobile device ownership, and physical activity level. A similar pattern emerged in the binary logistic regression model using the same four predictors, with the ordering of the Wald statistics mirroring the ANN-based importance ranking. This convergence across methods represents one of the most notable findings of the study, suggesting that risk classification may be shaped not only by access to technology but also, and perhaps more prominently, by school-related psychological pressure and socioemotional vulnerability. Nevertheless, the findings should be interpreted at an associative and predictive level. The cross-sectional design and internal validation framework do not support causal inference or individual-level clinical decision-making.

Academic expectation stress emerged as the dominant predictor in both analytical approaches, showing a normalized importance of 100.0% in the ANN model and the largest Wald statistic in the logistic regression analysis. This finding is strongly consistent with recent evidence suggesting that academic pressure may constitute a central psychosocial context for problematic social media use among adolescents. In a three-level meta-analysis of 49 studies including 189,483 adolescents, Chen et al. (2025) reported a positive association between academic stress and problematic internet use and emphasized that problematic internet use may function as a maladaptive coping strategy under conditions of intense academic pressure. Similarly, Li et al. (2025b), in a meta-analysis involving 34,558 adolescents, reported a strong positive association between perceived stress and mobile phone addiction. Together, these large-scale syntheses place the prominence of academic expectation stress observed in the present study within the broader adolescent literature rather than suggesting that it is merely a sample-specific finding.

However, academic stress does not appear to carry the same weight across all forms of digital addiction (Chen et al., 2025). For example, Wang et al. (2025b), using a two-stage SEM-ANN approach to examine smartphone addiction among university students, reported that academic anxiety was not the strongest direct predictor; instead, negative metacognitions together with future-related and social anxiety formed a more prominent predictive pattern. This difference highlights the importance of developmental context. During the high school years, examinations, transition to higher education, expectations from parents and teachers, and uncertainty about the future are more central features of daily life. Academic expectation stress may therefore play a more prominent role in digital escape or emotion-regulation behaviors among high school students than the more diversified sources of anxiety typically observed in university samples. This interpretation should be regarded not as evidence of a causal mechanism, but as a developmentally plausible explanation of the present finding.

The second-place ranking of loneliness further supports the importance of socioemotional vulnerability in problematic social media use. In a three-wave longitudinal study conducted over one year, Wu et al. (2024) found that loneliness and problematic social media use prospectively predicted one another over time. Drawing on a more recent and substantially broader evidence base, Feng et al. (2026), in a meta-analysis of 59 studies including 81,344 adolescents and young adults, identified a moderate and consistent association between problematic social media use and loneliness, whereas the association between time spent on social media alone and loneliness was very small. This distinction is particularly relevant to the present study: in explaining risk, the psychological function served by social media and the extent to which its use develops into a problematic pattern may be more informative than simply how much time individuals spend online (Hilty et al., 2023).

In this context, the relatively high importance of loneliness in the ANN model is consistent with the view that social media may function, for some adolescents, as a space that compensates for unmet needs for belonging, acceptance, and interpersonal closeness. However, social compensation does not necessarily lead to protective outcomes; problematic use may also sustain loneliness by increasing withdrawal from face-to-face relationships. In their systematic review of longitudinal risk factors for problematic social

media use among young people, Pazdur et al. (2025) identified poor peer relationships, negative affect, and mental health problems as recurring domains of risk. Accordingly, school-based prevention programs may need to move beyond messages focused solely on “using less social media” and instead strengthen protective processes such as peer connectedness, social support, school belonging, and face-to-face interpersonal skills.

Mobile device ownership ranked third in the model. This finding suggests that access does not constitute an explanation independent of psychosocial factors, but may broaden the behavioral context in which problematic use can develop. Ownership of a personal device may make use less dependent on parental or shared-device supervision, facilitate continued online access across different times of the day, and allow social media use to become more readily embedded in daily routines. Barzilay et al. (2026), using the ABCD sample of 10,588 early adolescents, found smartphone ownership to be associated with higher odds of depression, obesity, and insufficient sleep, and also showed that earlier device acquisition was associated with some adverse health outcomes. Yılmaz and Özkan (2026) similarly reported, in a sample of 1,971 adolescents, that excessive technology use and social media disorder should be considered together with individual, family, and school-related factors. Therefore, device ownership should not be interpreted here as a standalone “cause,” but rather as an indicator of access and autonomy that may facilitate the translation of psychosocial risk into behavior.

Although physical activity showed the lowest normalized importance among the four predictors, it remained relevant to the model and also made a statistically significant contribution in the logistic regression analysis. This pattern suggests that physical activity may function less as a direct and dominant risk indicator of problematic social media use and more as an indirect protective process related to lifestyle and emotion regulation. In a study of 3,247 adolescents, Wang et al. (2025a) found that physical activity was negatively associated with problematic social media use and that depressive symptoms may mediate this relationship. Niemistö et al. (2026), combining BSMAS scores with objective data, further reported that problematic social media use was associated with depressive and anxiety symptoms and that moderate-to-vigorous physical activity could buffer the adverse association with anxiety, particularly among girls. Considered together with these findings, the normalized importance value of 35.9% observed in the present study should not be interpreted as indicating that physical activity is unimportant, but rather that it provides a lower yet complementary predictive contribution relative to the other psychosocial variables.

The analytical findings of the present study are also noteworthy when considered in relation to the emerging literature. In recent years, ANN and other machine learning approaches have increasingly been used in behavioral addiction research to capture nonlinear patterns. Chen and Zhang (2024) and Li et al. (2025a) employed SEM-ANN approaches in university samples to examine the relative contributions of stress, self-control, anxiety, psychological resilience, and cognitive-behavioral factors to internet addiction. In a SEM-ANN study Wang et al. (2025b), used normalized ANN importance values to establish a priority ranking among psychological variables. In an adolescent sample, Göger et al. (2026) demonstrated the applicability of machine learning for classifying multiple-screen addiction. Within this

context, the present study makes a methodological contribution to the literature by evaluating psychosocial and behavioral variables within the same classification framework among high school students and by complementing the ANN findings with an interpretable logistic regression model.

The ANN model achieved an AUC of .971 in the test subset, indicating strong discrimination between the risk classes within the current dataset. However, the fact that the same numerical AUC was obtained for the logistic regression model should not be interpreted as evidence that the two methods were equivalent or that neither outperformed the other. Logistic regression performance was calculated on the full sample used to fit the model, whereas ANN performance was based on SPSS's internal test subset. More importantly, the ANN test subset was also incorporated into the stopping rule. Accordingly, the ANN AUC of .971 should be interpreted as an indicator of strong internal discriminative performance rather than independent external validation. Cross-validation and repeated resampling strategies are increasingly used in contemporary ANN applications; for example, Wang et al. (2025b) applied 10-fold cross-validation in their SEM-ANN study. Future research should therefore validate the present model in independent school and city samples and directly compare logistic regression and ANN within the same evaluation folds.

The fact that logistic regression and ANN produced the same predictor ranking provides a useful indication that the findings were not specific to a single modeling technique. Nevertheless, the metrics generated by the two approaches serve different inferential purposes. Wald statistics and ORs reflect the statistical contribution of coefficients within a parametric model, whereas normalized ANN importance reflects relative predictive contribution within a nonlinear network structure. Their numerical magnitudes should therefore not be compared directly. A strength of the present study is that, rather than treating these metrics as interchangeable, it examined whether the same overall predictor hierarchy emerged across two distinct analytical frameworks. In particular, the fact that academic expectation stress ranked first in both approaches provides converging evidence for the importance of school-related psychological burden in this sample, independent of the specific analytical method used.

Practical Implications

The findings suggest that school-based prevention efforts should move beyond one-dimensional approaches focused solely on reducing screen time. The clear prominence of academic expectation stress in the model supports the systematic assessment of examination- and performance-related pressure within school counseling and psychological support services, together with efforts to strengthen stress management, realistic goal setting, emotion regulation, and adaptive coping skills. The second-place ranking of loneliness further indicates that peer connectedness, school belonging, social support, and opportunities for safe face-to-face interaction should be incorporated as core components of digital well-being programs.

The findings regarding mobile device ownership and physical activity also suggest that behavioral regulation at both the family and school levels should not be overlooked. Rather than relying on strict

prohibitions on personal devices, more sustainable targets may include age-appropriate limits on use, regulation of nighttime use, stronger parent–adolescent communication, and the development of digital self-regulation skills. Similarly, increasing access to regular physical activity may provide alternative opportunities for structured leisure and face-to-face peer interaction. However, neither the current ANN model nor the BSMAS ≥ 19 threshold should be used as a clinical diagnostic tool. The model should instead be regarded as a risk-classification approach that requires further validation. If applied in school settings, it should be supported by multi-source assessment procedures, including individual interviews, evaluation of functional impairment, and referral to mental health professionals when indicated.

Strengths, Limitations, and Future Research

This study has several strengths. First, variables operating at different levels, including academic stress, loneliness, access to technology, and physical activity, were examined within the same model in a sample of 899 high school students. Second, model performance was evaluated not only using overall accuracy, but also with metrics that are more informative in the presence of class imbalance, including sensitivity, specificity, precision, F1 score, balanced accuracy, and AUC. Third, complementing the ANN findings with a binary logistic regression model based on the same predictors made it possible to examine the consistency of the predictor ranking across analytical approaches. Finally, explicitly defining the BSMAS cutoff as a screening threshold for risk rather than as a clinical diagnostic criterion made the limits of measurement-based interpretation more transparent.

Nevertheless, the findings should be interpreted in light of several limitations. First, because the study was cross-sectional, it cannot be determined whether academic expectation stress, loneliness, physical activity, or device ownership preceded problematic social media use. In particular, the bidirectional relationship between loneliness and problematic social media use demonstrated in longitudinal research suggests the possibility of reverse and reciprocal effects (Wu et al., 2024). Second, the fact that the main variables were largely based on self-report measures may have introduced common method bias as well as recall and social desirability effects. Third, because the sample was drawn from high schools in a single provincial center, the generalizability of model performance to different socioeconomic and cultural contexts is limited.

Fourth, the BSMAS assesses problematic use specifically related to social media; therefore, the findings concerning “risk for problematic social media use” should not be generalized to internet use, gaming, short-form video use, or other forms of digital behavior. Although dichotomizing the BSMAS total score at ≥ 19 is practical for screening purposes, doing so reduces information contained in the continuous score and may make the results sensitive to the selected cutoff. Fifth, ANN performance was based on a single random training–test split, and because the test subset was also used as part of the stopping rule, it did not constitute an independent holdout validation sample. The absence of k-fold cross-validation, repeated train–test splits, and external-sample validation leaves uncertainty regarding the extent to which the reported performance would be maintained in new samples. Similarly, because the

classification performance of the logistic regression model was calculated on the same full sample used to fit the model, it should be regarded as a within-sample estimate of performance.

Sixth, mobile device ownership is a binary and relatively coarse indicator of access. More fine-grained digital behavior variables, such as age at device acquisition, daily duration of use, nighttime use, platform type, notification frequency, and purpose of use, were not included in the model. The self-reported assessment of physical activity may also be more susceptible to measurement error than objective movement data. Future studies could incorporate objective indicators, such as screen-time logs, passive digital traces, and accelerometer-derived activity data, alongside psychosocial measures to develop models with greater ecological validity. It will also be important to examine subgroup performance and model fairness across gender, grade level, school type, and socioeconomic status.

Future research should employ multicenter and longitudinal designs; conduct sensitivity analyses using the BSMAS both as a continuous score and across alternative risk thresholds; compare ANN and logistic regression within the same cross-validation folds; and report probability-calibration metrics such as calibration curves and the Brier score. More interpretable machine learning approaches could also be incorporated to explain individual predictions. However, explainability techniques should be treated as tools for understanding model behavior rather than as indicators of causal effects, particularly in cross-sectional data. Following such validation, it would be possible to assess more reliably whether the model could be developed into a low-cost early-warning approach for use in school psychological counseling services.

Conclusion

This study showed that risk for problematic social media use among high school students cannot be adequately explained by a single indicator of technology use, but may be better understood as a pattern jointly shaped by academic, social, and behavioral factors. Academic expectation stress emerged as the most prominent predictor across both analytical approaches, followed by loneliness, while mobile device ownership and physical activity level provided lower but complementary predictive contributions. The high discriminative performance of the MLP-ANN model in the test subset, together with the convergence between the predictor hierarchy observed in logistic regression and the ANN-based importance ranking, indicates a consistent analytical pattern across methods.

The main implication of the study is that efforts to prevent problematic social media use among adolescents should not focus solely on restricting device use. Helping students cope with academic pressure, reducing loneliness, strengthening social connectedness, and promoting a physically active lifestyle should also be considered important components of preventive interventions. However, the cross-sectional design and the lack of independent external validation of the classification model represent important limitations. Accordingly, the findings should not be used for diagnostic purposes or interpreted as causal risk estimates, but rather as evidence that may inform future longitudinal and multicenter research. If the model is subsequently validated in independent samples, explainable

predictive models based on psychosocial variables may have potential utility in school-based early identification and preventive mental health initiatives.

Abbreviations

ANN
Artificial neural network
MLP
Multilayer perceptron
BSMAS
Bergen Social Media Addiction Scale
AUC
Area under the receiver operating characteristic curve
ROC
Receiver operating characteristic
OR
Odds ratio
CI
Confidence interval
SE
Standard error
IPAQ-SF
International Physical Activity Questionnaire–Short Form
MET
Metabolic equivalent of task
UCLA
University of California, Los Angeles.

Declarations

Ethics Approval And Consent To Participate

Ethical approval was obtained from the Ethics Committee of Scientific Research in Social and Human Sciences at Karamanoğlu Mehmetbey University (Decision No. 03-2026/86). All required institutional permissions were obtained prior to data collection. Participation was voluntary, and informed consent was obtained from the participating students and their parents/legal guardians prior to data collection.

Data Availability

The datasets generated and/or analyzed during the current study are not publicly available due to privacy and ethical considerations concerning the participating students. De-identified data may be made

available by the corresponding author upon reasonable request, subject to applicable ethical and institutional restrictions.

Consent to Participate

Participation in the study was voluntary. Informed consent was obtained from all participating students and their parents/legal guardians prior to data collection.

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Figures

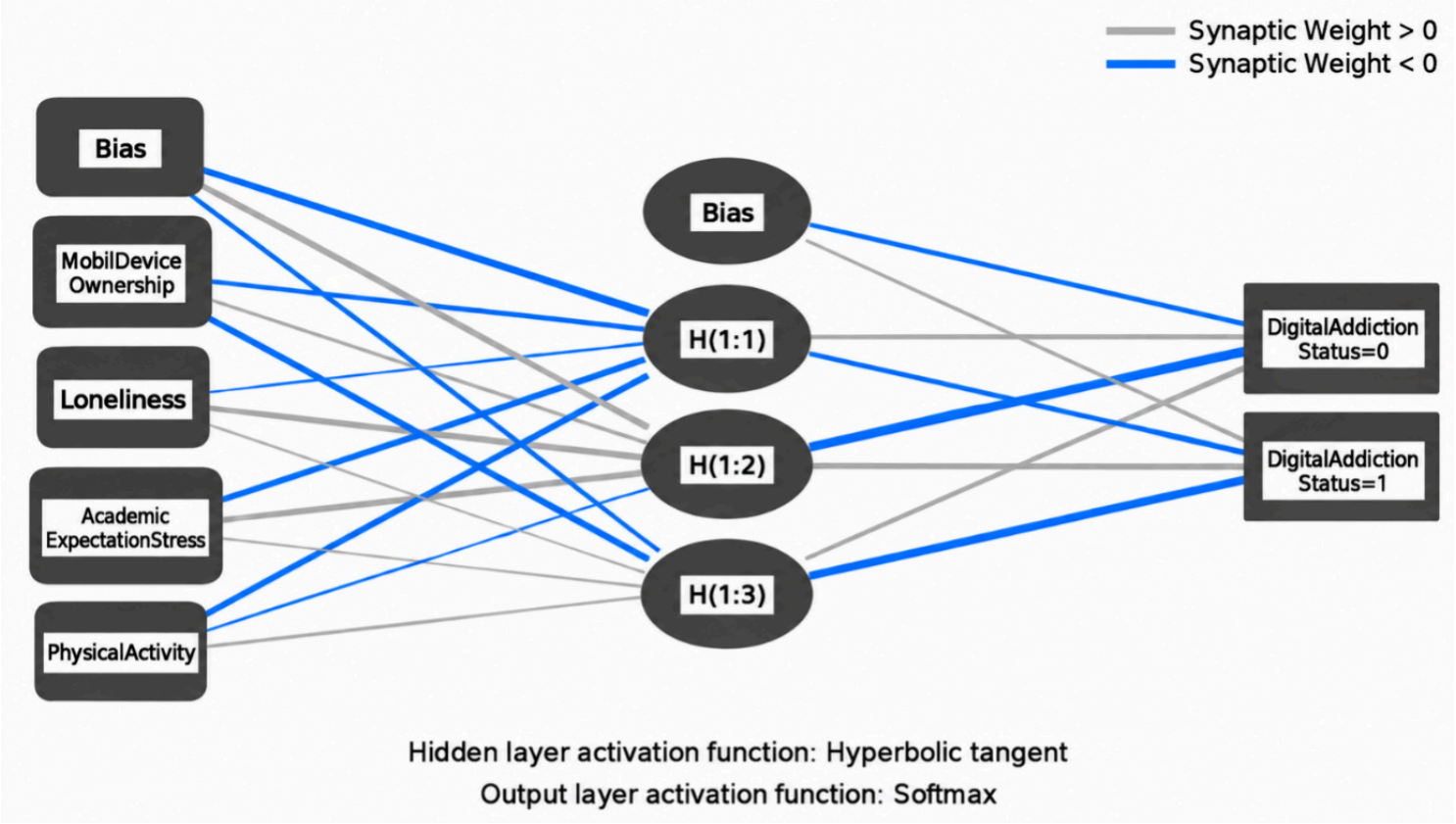


Figure 1

Architecture of the multilayer perceptron artificial neural network used to classify BSMAS-based risk status

Note. The model consisted of four standardized input variables, one hidden layer with three neurons, and two output units. The hidden layer used the hyperbolic tangent activation function and the output layer used Softmax.

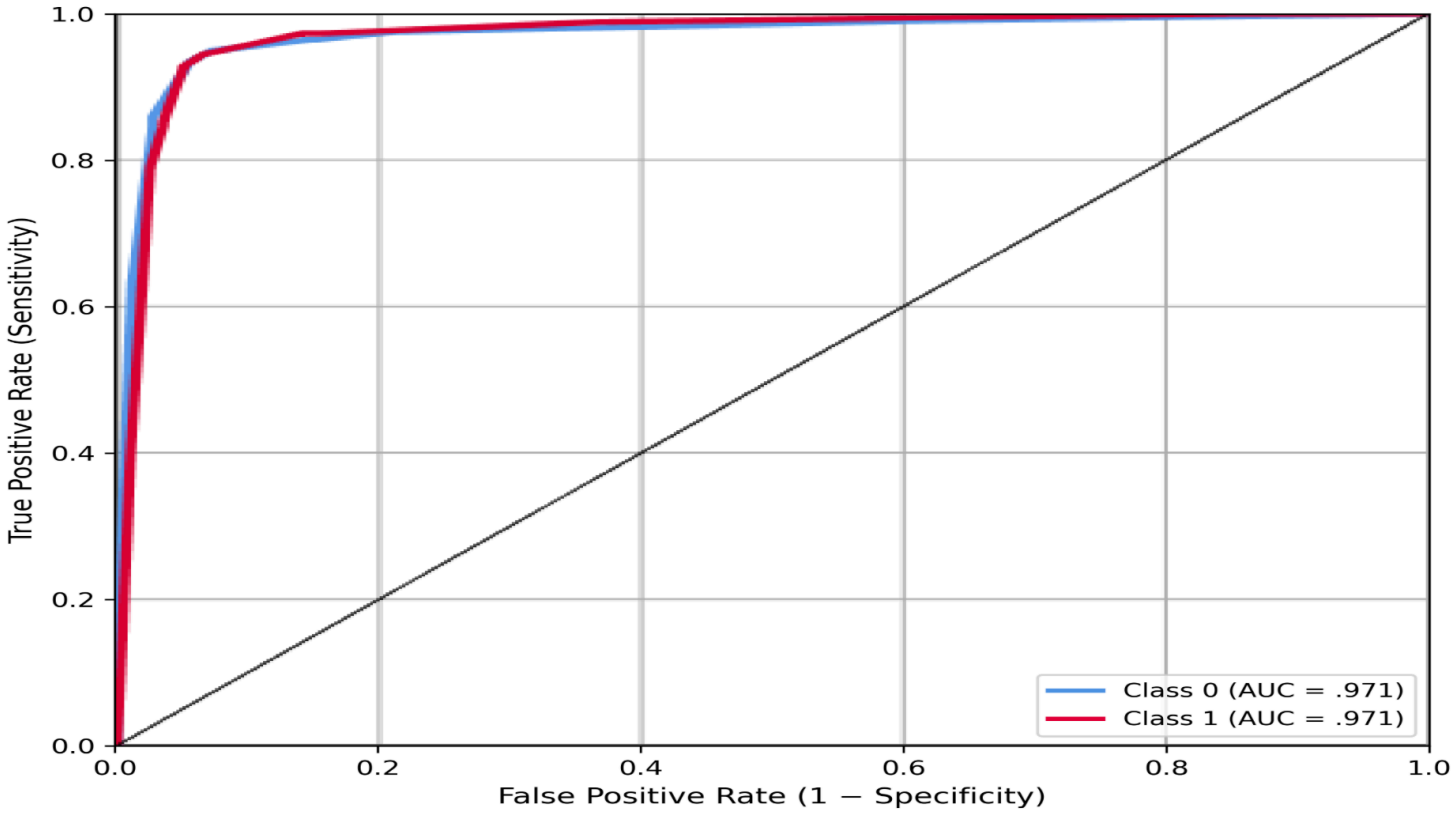


Figure 2

Receiver operating characteristic curves for the MLP-ANN model

Note. AUC = .971 for both risk-status categories. Class 0 = not at risk (BSMAS < 19); Class 1 = at risk for problematic social media use (BSMAS >= 19). The diagonal line represents chance-level discrimination.

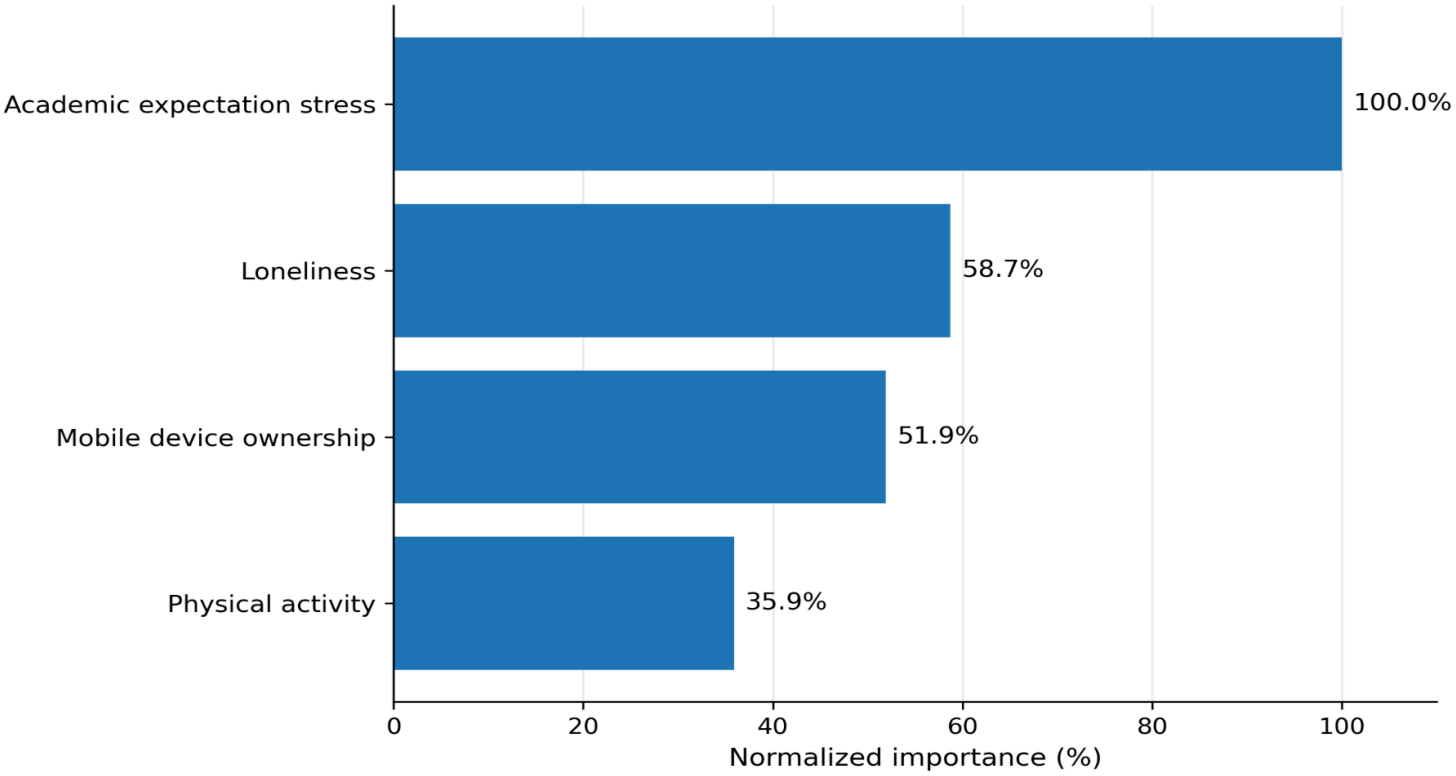


Figure 3

Normalized importance of predictor variables in the MLP-ANN model

Note. The predictor with the highest importance was standardized to 100%, and the normalized importance of the remaining variables was expressed relative to this reference.