

Deep Neural Network Prediction of Depression Risk Among Young Adults Based on Psychological, Sleep, Lifestyle, and Social Variables

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ABSTRACT

Objective: This study aimed to develop and evaluate a deep neural network model for predicting elevated depression risk among young adults in Canada using psychological, sleep-related, lifestyle, and social variables.

Methods and Materials: This cross-sectional predictive study included 1,042 Canadian young adults aged 18–35 years. Depression risk was assessed using the Patient Health Questionnaire-9, with scores ≥ 10 indicating elevated risk. Predictors included perceived stress, anxiety symptoms, self-esteem, loneliness, resilience, sleep quality, sleep duration, sleep-onset latency, physical activity, sedentary behavior, screen time, perceived social support, financial strain, and meaningful social interactions. Data were divided into training ($n = 729$), validation ($n = 156$), and independent test ($n = 157$) sets using stratified sampling. A feedforward deep neural network with three hidden layers was trained using the Adam optimizer and binary cross-entropy loss. Performance was evaluated using accuracy, sensitivity, specificity, precision, F1 score, ROC-AUC, PR-AUC, and Brier score. Logistic regression, random forest, and gradient boosting were used as benchmark models, and SHAP values were applied to interpret predictor importance.

Findings: The deep neural network achieved an accuracy of 0.87, sensitivity of 0.84, specificity of 0.89, precision of 0.82, F1 score of 0.83, ROC-AUC of 0.93, PR-AUC of 0.89, and Brier score of 0.101 in the independent test set. It outperformed logistic regression, random forest, and gradient boosting. The strongest predictors were generalized anxiety symptoms, perceived stress, low social support, low self-esteem, loneliness, poor sleep quality, financial strain, low resilience, shorter sleep duration, and greater sedentary time. Nonlinear effects and cross-domain interactions were also identified.

Conclusion: Depression risk among young adults can be predicted with high accuracy by integrating psychological, sleep, lifestyle, and social variables within an interpretable deep neural network framework.

Keywords: depression risk; deep neural network; young adults; sleep quality; psychological distress; lifestyle; social support; machine learning

1. Introduction

Depression is one of the most consequential mental health problems affecting young adults, with substantial implications for emotional functioning, academic achievement, occupational performance, interpersonal relationships, physical health, and long-term quality of life. The transition from adolescence to adulthood is characterized by rapid changes in social roles, educational and occupational demands, financial responsibilities, relationship formation, and independent living, all of which may increase vulnerability to psychological distress. Young adulthood is also a period in which behavioral routines related to sleep, technology use, physical activity, eating patterns, and social interaction often become irregular. These factors may interact with psychological predispositions and environmental stressors in ways that increase the likelihood of depressive symptoms. Recent evidence has emphasized that depression among young adults should not be understood as the result of a single isolated risk factor, but rather as a multidimensional outcome emerging from complex interactions among psychological, behavioral, sleep-related, circadian, lifestyle, and social determinants (Merlo et al., 2026; Purnawati et al., 2022; Ray, 2023). This multidimensional nature creates a strong rationale for predictive approaches capable of integrating numerous potentially interdependent risk indicators simultaneously.

Sleep has increasingly been recognized as a central component of mental and physical health and as an important determinant of psychological resilience. Contemporary perspectives regard sleep not merely as a passive biological state but as a fundamental health behavior influenced by social context, environmental exposure, lifestyle, technology use, and circadian regulation. The recently proposed One Sleep Health framework highlights the importance of elevating sleep to a global health priority and understanding sleep health through an integrated perspective that encompasses biological, behavioral, societal, and environmental dimensions (Tahmasian et al., 2026). This framework is particularly relevant to young adults because this age group frequently experiences insufficient sleep, delayed sleep timing, irregular schedules, prolonged screen exposure, and competing academic, occupational, and social demands. Sleep disruption may influence mood regulation, cognitive control, stress responsiveness, and interpersonal functioning, thereby

contributing to the development or maintenance of depressive symptoms.

A growing body of evidence demonstrates that sleep duration, sleep quality, insomnia symptoms, and circadian timing are closely associated with mental health in young populations. Research among university students has shown that sleep problems frequently coexist with anxiety, depressive symptoms, and other forms of psychological distress (Kim et al., 2022). Sleep disturbance may also become more pronounced during periods of environmental instability and psychosocial stress. The COVID-19 pandemic, for example, produced widespread alterations in daily routines, social interactions, screen use, work and study schedules, and exposure to stress, with sleep disturbance becoming a prominent concern alongside increasing mental health difficulties (Spicuzza, 2021). Broader reviews of pandemic-related mental health outcomes among children, adolescents, and young adults similarly indicated substantial increases in psychological distress and highlighted the need for accessible and scalable approaches to early mental health identification (Purnawati et al., 2022). These observations reinforce the importance of including sleep variables in predictive models of depression risk.

Circadian rhythm characteristics represent another important dimension of mental health vulnerability. Young adults commonly exhibit delayed sleep timing, evening preference, and irregular sleep-wake patterns, particularly in educational settings where social and academic schedules may conflict with biological circadian tendencies. Delayed sleep-wake phase disorder has been identified as a meaningful problem in young adults and university students, with associations involving sleep insufficiency, impaired functioning, and psychological difficulties (Sivertsen et al., 2021). Related research has shown that delayed sleep-wake phase patterns in younger generations are linked to specific maladaptive sleep behaviors and scheduling practices (Futenma et al., 2023). Chronotype itself has also been increasingly examined in relation to depressive symptomatology. Evidence suggests that evening chronotype may be associated with heightened vulnerability to depression through mechanisms involving circadian misalignment, sleep restriction, impaired emotion regulation, and altered neurobiological functioning (Zhao et al., 2025). More broadly, chronotype and circadian rhythm disturbances have been implicated in multiple psychiatric disorders, suggesting that the temporal organization of sleep and wakefulness may be a transdiagnostic component of

mental health risk (Zou et al., 2022). Circadian management has therefore been proposed as a potentially important strategy for improving mental health among college students (Yeom & Lee, 2024).

The relationship between sleep and depression is not limited to duration and circadian timing. Sleep deprivation and insomnia may affect emotional reactivity, cognitive processing, reward systems, and stress regulation, thereby creating pathways through which sleep disturbance contributes to mental health problems. Evidence concerning adolescents and younger populations indicates that insufficient sleep and insomnia are associated with significant psychological consequences and may increase susceptibility to mood disturbances (Uccella et al., 2023). Among college students, sleep difficulties may also impair academic functioning through the combined influence of psychological distress, substance use, and loneliness, demonstrating that sleep-related impairment occurs within a broader network of psychosocial conditions (Chung, 2025). In addition, psychological characteristics can themselves influence sleep quality. Research among university students has demonstrated that psychological factors contribute substantially to variation in sleep quality, indicating a reciprocal relationship in which distress can disrupt sleep and disturbed sleep can further intensify emotional difficulties (Anandavelu et al., 2022).

Sleep-related behaviors and bedtime routines may provide additional information about risk profiles. College students use a wide range of behavioral strategies to initiate sleep, some of which may be adaptive and others potentially counterproductive. Comprehensive assessment of bedtime routines has shown that sleep onset is shaped by habitual behaviors, environmental conditions, cognitive arousal, technology use, and self-regulatory strategies (Meneo et al., 2024). Electronic device use is especially relevant in contemporary young adults. Extensive exposure to smartphones, computers, gaming devices, and social media platforms may delay bedtime, suppress sleep-promoting physiological processes, increase cognitive stimulation, and contribute to irregular sleep schedules. Reviews of electronic device use among young people have emphasized its potential adverse effects on sleep timing, duration, and quality (Sysło et al., 2024). Digital addiction has similarly been linked with sleep disturbances, highlighting the possibility that problematic technology use may function as both a lifestyle risk factor and an indirect contributor to depressive symptoms (Dresp & Hutt, 2022).

At the same time, mobile technologies may provide opportunities for scalable mental health assessment. Smartphones continuously generate behavioral and sensor-based information related to activity, mobility, sleep, communication, and daily routines. A review of smartphone sensing in adults and young adults has suggested that digital phenotyping may offer feasible methods for tracking insomnia, depression, and anxiety, although methodological and ethical challenges remain (Alamoudi et al., 2023). The increasing availability of high-dimensional digital and self-reported data creates an opportunity to move beyond conventional single-variable screening and toward computational models that identify complex combinations of risk markers. Such an approach may be particularly valuable in depression because different individuals can reach similar levels of depressive symptomatology through distinct combinations of stress, sleep disruption, social isolation, behavioral inactivity, anxiety, and financial or academic difficulties.

Lifestyle behaviors are also closely connected with mental health. Contemporary lifestyle medicine increasingly recognizes physical activity, sleep, social connection, nutrition, substance-use reduction, and stress management as important components of depression prevention and treatment. Expert consensus has emphasized that lifestyle interventions can play a clinically meaningful role in major depressive disorder and should be considered alongside established mental health treatments (Merlo et al., 2026). Exercise may be particularly important in young adults because it influences mood, stress regulation, sleep architecture, circadian stability, and cognitive functioning. Recent evidence concerning college students has indicated that exercise may improve sleep health through both physiological and psychological mechanisms, supporting the integration of physical activity and sleep variables in mental health research (Chen et al., 2025). Conversely, insufficient activity, prolonged sedentary time, and excessive screen exposure may form a cluster of behaviors associated with poorer psychological well-being.

Time spent outdoors may represent another relevant behavioral factor. Exposure to outdoor environments can affect light exposure, physical activity, circadian synchronization, social interaction, and subjective well-being. Research conducted before and during the COVID-19 pandemic demonstrated associations between time spent outdoors and sleep, optimism, happiness, and health outcomes (Schamilow et al., 2023). These findings suggest that environmental and behavioral patterns may operate

jointly rather than independently. Similarly, health behaviors linked to chronotype may extend beyond sleep itself. Research among university students has examined associations between sleep parameters, chronotype, and eating-disorder risk, illustrating that circadian patterns are embedded within broader behavioral systems involving eating, self-regulation, and health-related routines (Tomás Olivo Martins de et al., 2024). Thus, lifestyle variables may provide additional predictive value when considered together with psychological and sleep-related indicators.

Psychological distress is particularly important in models of depression risk because anxiety, stress, self-esteem, resilience, loneliness, and related constructs often show strong associations with depressive symptoms. Anxiety and depression frequently co-occur among university students, and research has demonstrated interconnected pathways through which anxiety and depressive symptoms may influence one another (Wen et al., 2022). The co-occurrence of anxiety and depression suggests that risk models should not treat these variables as unrelated diagnostic domains but rather as overlapping dimensions of emotional vulnerability. Psychological distress may also affect cognitive functioning, sleep, interpersonal behavior, and academic performance, contributing to a reinforcing cycle of impairment. In young adults, these psychological variables can fluctuate rapidly in response to academic pressure, uncertainty about employment, relationship difficulties, financial strain, and reduced social support.

Loneliness and social disconnection are especially important because they may amplify the effects of stress and sleep disturbance. Young adults may experience social isolation even when they are highly connected through digital platforms, and perceived loneliness can remain clinically important despite frequent online interaction. Research has shown that loneliness is associated with maladjustment in young adults, while sleep quality and physiological regulatory capacity may provide protective effects (Philbrook et al., 2023). This suggests that social and sleep-related variables may interact in ways that influence psychological adjustment. Social capital has also been associated with sleep duration in population research, supporting the broader proposition that social resources and sleep health are interconnected (Nutakor et al., 2023). Although such findings have been reported in populations beyond young adulthood, they underscore the relevance of social integration, perceived support, and interpersonal resources in understanding health behaviors and psychological outcomes.

Positive psychological constructs may also influence sleep and depression vulnerability. Gratitude, for instance, has been examined in relation to sleep quality among young adults, with findings suggesting that positive emotional orientations may be associated with healthier sleep experiences (Narang, 2024). These associations support a broader model in which depression risk reflects not only the accumulation of vulnerabilities but also the relative absence or presence of protective psychological resources. Self-esteem, resilience, optimism, gratitude, and social support may buffer the effects of stress, loneliness, and sleep disturbance, creating complex nonlinear relationships that traditional linear models may not fully capture.

The consequences of combined depression and sleep insufficiency can be particularly serious. Population-based evidence among college students has shown that depression and insufficient sleep may jointly contribute to self-harm behaviors, indicating that co-occurring risk factors may have greater clinical significance than either factor considered alone (Hua et al., 2023). This is highly relevant for predictive research because the primary goal of risk estimation is not simply to classify current symptoms, but to identify individuals whose multidimensional profiles suggest increased vulnerability to adverse outcomes. The ability to detect risk based on interacting psychological, sleep, behavioral, and social characteristics could support earlier screening and more targeted preventive strategies.

Sleep also influences cognitive functioning, which may indirectly contribute to depression vulnerability by affecting academic performance, decision-making, emotion regulation, and perceived competence. Recent research among college students has demonstrated associations between sleep and multiple domains of cognitive functioning, reinforcing the importance of sleep as a foundational determinant of daily performance (Xu et al., 2025). Poor sleep may therefore contribute to a cascade in which cognitive inefficiency increases academic or occupational stress, reduced performance lowers self-efficacy, and psychological distress further disrupts sleep. Similarly, associations between chronotype and depressive symptoms have been documented in other adult populations, indicating that circadian preference may be related to depressive symptomatology across different contexts (Wang et al., 2023). These findings support the inclusion of sleep and circadian variables alongside more conventional psychological indicators.

Young adults also face a range of contextual challenges that may intensify psychological burden. University

students, in particular, may experience academic overload, uncertain career prospects, social comparison, irregular schedules, economic pressures, and difficulties maintaining stable health routines. Studies focusing on urban undergraduate populations have emphasized the importance of understanding mental health and well-being within the broader context of educational and social demands (Ray, 2023). The mental health emergency observed among university students following the COVID-19 pandemic further demonstrated how quickly psychological vulnerability can increase when social disruption, health uncertainty, and educational instability occur simultaneously (Patrono et al., 2022). Such observations make prediction particularly important because traditional screening conducted only after substantial symptom development may miss opportunities for earlier intervention.

Intervention research also highlights the importance of modifiable sleep behaviors. Systematic review and meta-analytic evidence indicates that behavior-change theory has been incorporated into sleep interventions for emerging adults, supporting the idea that sleep-related behaviors can be modified through structured strategies (Pegado et al., 2023). This is relevant to prediction because a useful risk model should ideally identify not only who is at risk but also which modifiable domains contribute most strongly to that risk. Variables such as sleep regularity, physical activity, sedentary behavior, social support, screen exposure, perceived stress, and bedtime routines may therefore have greater practical relevance than static demographic characteristics.

Taken together, the available literature shows that depression risk in young adults is shaped by a complex network of mutually reinforcing factors involving psychological distress, anxiety, loneliness, sleep quality, sleep duration, insomnia, circadian timing, technology use, activity patterns, social connection, and broader lifestyle conditions (Futenma et al., 2023; Kim et al., 2022; Philbrook et al., 2023; Syslo et al., 2024). However, much of the existing research has examined these variables separately or through conventional regression-based approaches that assume relatively simple and predominantly linear relationships. Such methods remain valuable for estimating interpretable associations but may be limited when predictors interact, show threshold effects, or contribute differently across subgroups. Deep neural networks offer an alternative approach because they can model high-dimensional, nonlinear, and interactive relationships without requiring all functional forms to be specified in advance. For

depression risk prediction, this flexibility may be particularly advantageous because psychological, sleep, lifestyle, and social variables are likely to influence one another rather than operate independently.

The growing availability of multidomain behavioral and psychosocial data therefore creates a strong methodological rationale for applying deep learning to depression-risk classification. A neural network can simultaneously incorporate stress, anxiety, self-esteem, loneliness, resilience, sleep quality, sleep duration, circadian behaviors, physical activity, sedentary behavior, screen exposure, social support, financial strain, and related contextual indicators, potentially identifying patterns that are difficult to detect using traditional statistical models. Moreover, interpretability methods can be applied after model development to identify the variables that contribute most strongly to predicted risk, thereby improving the clinical and public-health relevance of the model. This is especially important because prediction without interpretability may have limited practical value in mental health contexts where researchers and practitioners need to understand which modifiable factors are driving elevated risk.

Accordingly, the aim of the present study was to develop and evaluate a deep neural network model for predicting elevated depression risk among young adults in Canada using an integrated set of psychological, sleep-related, lifestyle, and social variables.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a quantitative, cross-sectional, predictive design to develop and evaluate a deep neural network model for estimating depression risk among young adults based on psychological, sleep-related, lifestyle, and social variables. The study population consisted of young adults residing in Canada who were between 18 and 35 years of age at the time of data collection. Participants were recruited from different Canadian provinces and territories through online advertisements, university and college mailing lists, community-based social media platforms, and electronic research participation notices in order to obtain a heterogeneous sample with respect to educational status, employment status, living conditions, and socioeconomic background. A total of 1,286 individuals initially accessed the online survey. After removal of respondents who did not meet the age or residency criteria, submitted substantially incomplete questionnaires, provided duplicate responses, or

showed invalid response patterns, the final analytical sample consisted of exactly 1,042 young adults. Eligibility criteria included being 18–35 years of age, currently residing in Canada, having sufficient proficiency in English to understand the study questionnaires, providing informed consent, and completing the principal study measures. Individuals were excluded when they failed to complete the depression measure or had more than 20% missing data across the predictor variables required for model development. Participation was voluntary, and respondents were informed about the purpose of the study, confidentiality of their data, their right to withdraw before submitting the questionnaire, and the absence of any effect of participation or nonparticipation on access to services. No directly identifying information was incorporated into the analytical dataset. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki, and electronic informed consent was obtained from all participants before access to the research questionnaires was granted.

2.2. Measures

Data were collected using a structured online questionnaire comprising demographic characteristics, psychological indicators, sleep variables, lifestyle-related factors, social variables, and a standardized measure of depressive symptoms. Depression risk, which constituted the primary outcome variable, was assessed using the Patient Health Questionnaire-9 (PHQ-9). The PHQ-9 consists of nine items corresponding to the major symptom domains of depressive disorders and asks participants to indicate the frequency with which they experienced each symptom during the preceding two weeks. Each item is rated on a four-point scale ranging from 0, indicating “not at all,” to 3, indicating “nearly every day,” resulting in a total score ranging from 0 to 27, with higher scores representing greater depressive symptom severity. For predictive classification, participants with a PHQ-9 score of 10 or higher were categorized as being at elevated risk of clinically significant depression, whereas those scoring below 10 were categorized as being at lower risk. The continuous PHQ-9 score was additionally retained for descriptive analyses and supplementary assessment of symptom severity. Psychological predictors included perceived stress, generalized anxiety symptoms, self-esteem, loneliness, and perceived psychological resilience. Perceived stress was assessed using the 10-item Perceived Stress Scale, which

evaluates the degree to which individuals perceive their recent life circumstances as unpredictable, uncontrollable, and overwhelming. Anxiety symptoms were measured using the seven-item Generalized Anxiety Disorder scale, with higher scores indicating greater severity of anxiety symptoms. Self-esteem was evaluated using the Rosenberg Self-Esteem Scale, while loneliness was assessed with a brief version of the UCLA Loneliness Scale. Psychological resilience was measured using a validated brief resilience measure assessing participants’ perceived capacity to recover from stressful experiences and adapt to adversity.

Sleep-related information included average nightly sleep duration, perceived sleep quality, sleep-onset latency, frequency of nocturnal awakenings, daytime sleepiness, irregularity of sleep schedules, and symptoms of insomnia. Overall sleep quality was measured using the Pittsburgh Sleep Quality Index, which captures subjective sleep quality and multiple behavioral dimensions of sleep during the preceding month. Participants also reported their typical bedtime and wake time on weekdays and weekends, allowing the derivation of sleep duration and variability indicators. Lifestyle variables included frequency of moderate and vigorous physical activity, sedentary time, daily screen exposure outside occupational or academic requirements, smoking status, alcohol consumption frequency, dietary regularity, frequency of fruit and vegetable consumption, consumption of energy drinks or highly caffeinated beverages, and perceived balance between work or study demands and leisure activities. Physical activity was assessed by asking participants about the frequency and approximate duration of moderate- and vigorous-intensity activity during a typical week, and total weekly activity was subsequently calculated. Social predictors included perceived social support, relationship status, living arrangement, frequency of meaningful social interaction, perceived social isolation, satisfaction with interpersonal relationships, participation in organized social or community activities, and perceived financial strain. Perceived social support was assessed using the Multidimensional Scale of Perceived Social Support, covering support received from family, friends, and significant others. Demographic and contextual variables included age, sex, gender identity, educational attainment, student status, employment status, household income category, province or territory of residence, urban or rural residence, immigration status, and living arrangement. All multi-item measures were scored according to their standard scoring procedures, and higher scores were interpreted

according to the direction of each respective construct. Prior to predictive modeling, categorical variables were converted into machine-readable indicator variables, while continuous variables were retained at their original measurement level and subsequently standardized.

2.3. Data Analysis

Data analysis was conducted using Python and established machine-learning libraries for preprocessing, neural network development, and statistical evaluation. Initial analyses included examination of data completeness, identification of duplicate cases, assessment of implausible values, descriptive statistics, and evaluation of the distribution of continuous variables. Missing values among predictor variables were handled within the preprocessing pipeline to minimize information leakage between model-development and evaluation datasets. Continuous variables with missing values were imputed using the median calculated exclusively from the training data, whereas categorical variables were imputed using the modal category. Continuous predictors were standardized to a mean of zero and a standard deviation of one based on parameters estimated in the training dataset, and categorical predictors were transformed using one-hot encoding. The complete sample of 1,042 participants was randomly divided into training, validation, and independent test subsets using stratified sampling based on depression-risk status in order to preserve the proportion of higher- and lower-risk participants across datasets. Seventy percent of the sample was allocated to the training set, corresponding to 729 participants, 15% to the validation set, corresponding to 156 participants, and the remaining 15% to the independent test set, corresponding to 157 participants. The training dataset was used for estimation of model parameters, the validation dataset was used for hyperparameter selection and control of overfitting, and the test dataset remained untouched until final model evaluation.

A feedforward deep neural network was developed to classify participants according to elevated depression risk. The input layer contained all psychological, sleep, lifestyle, social, and demographic predictors retained after preprocessing. The final architecture consisted of three fully connected hidden layers containing 128, 64, and 32 neurons, respectively. Rectified linear unit activation functions were used in the hidden layers because of their computational efficiency and capacity to model nonlinear relationships, while the output layer consisted of a single neuron with a

sigmoid activation function that generated an estimated probability of elevated depression risk ranging from 0 to 1. Dropout regularization was applied between hidden layers to reduce overfitting, and L2 weight regularization was incorporated into the network. The model was trained using the Adam optimization algorithm and binary cross-entropy as the loss function. Mini-batch training was performed, and the maximum number of training epochs was specified in advance; however, early stopping based on validation loss was used to terminate training when additional epochs no longer improved generalization performance. The network weights corresponding to the lowest validation loss were retained for final evaluation. Hyperparameters, including the number of hidden layers, number of neurons per layer, learning rate, dropout rate, batch size, and regularization strength, were selected according to validation performance rather than test-set results. Where imbalance between depression-risk categories was observed, class weights derived from the training sample were incorporated into the loss function to reduce bias toward the majority category.

Final predictive performance was evaluated exclusively in the independent test dataset. The principal discrimination metric was the area under the receiver operating characteristic curve, supplemented by accuracy, sensitivity, specificity, precision, F1 score, and the area under the precision-recall curve. Sensitivity was considered particularly important because the purpose of the predictive model was the identification of young adults who might be at elevated risk of depression rather than the establishment of a clinical diagnosis. Model calibration was examined by comparing predicted probabilities with observed depression-risk frequencies and by calculating the Brier score. The conventional probability threshold of 0.50 was examined for classification, while threshold-dependent performance was additionally evaluated to determine whether alternative thresholds provided a more appropriate balance between sensitivity and specificity. To provide a benchmark for evaluating the added value of nonlinear deep-learning methods, the performance of the deep neural network was compared with conventional logistic regression and selected machine-learning classifiers trained on the same predictors and data partitions. Feature contribution to the final neural network predictions was investigated using SHapley Additive exPlanations, which provided both global estimates of the relative contribution of individual variables and participant-level explanations of predicted depression risk. Particular attention was given to the relative predictive contributions of stress, anxiety, loneliness, self-esteem,

sleep quality, sleep duration, physical activity, sedentary behavior, social support, and perceived financial strain. Statistical tests used for descriptive and preliminary comparisons were two-tailed, with a significance level of $p < .05$, whereas evaluation of the predictive model was primarily based on discrimination, calibration, and generalization indices rather than null-hypothesis significance testing.

3. Findings and Results

A total of 1,042 young adults residing in Canada were included in the final analysis. Participants ranged in age from 18 to 35 years, with a mean age of 26.41 years ($SD = 4.83$). Of the total sample, 558 participants (53.55%) identified as women, 452 (43.38%) as men, and 32 (3.07%) identified as non-binary, gender-diverse, or another gender identity. Regarding educational attainment, 214 participants (20.54%) had completed high school or an equivalent qualification, 286 (27.45%) reported some college or university education, 391 (37.52%) held a bachelor's degree, and 151 (14.49%) held a postgraduate degree. A total of 436

participants (41.84%) were currently enrolled as full-time or part-time students, while 606 (58.16%) were not students. With respect to employment status, 512 participants (49.14%) were employed full-time, 236 (22.65%) were employed part-time, 158 (15.16%) were unemployed and actively seeking work, and 136 (13.05%) were not currently participating in the labor force. In terms of relationship status, 472 participants (45.30%) reported being single, 393 (37.72%) were in a committed relationship but not married, 147 (14.11%) were married or in a common-law partnership, and 30 (2.88%) were divorced, separated, or widowed. Most participants lived in urban or suburban areas, accounting for 873 individuals (83.78%), whereas 169 participants (16.22%) lived in rural or remote communities. Based on the predefined PHQ-9 cutoff score of 10 or higher, 372 participants (35.70%) were classified as being at elevated risk of clinically significant depression, while 670 participants (64.30%) were classified as being at lower risk. The mean PHQ-9 score in the total sample was 8.73 ($SD = 6.18$), indicating substantial variability in depressive symptom severity across participants.

Table 1

Descriptive Statistics of Psychological, Sleep, Lifestyle, and Social Variables in the Total Sample

Variable	M	SD	Minimum	Maximum
PHQ-9 depression score	8.73	6.18	0.00	27.00
Perceived stress	18.92	6.54	2.00	38.00
Generalized anxiety symptoms	7.41	5.37	0.00	21.00
Self-esteem	27.68	5.42	11.00	40.00
Loneliness	7.83	3.08	3.00	15.00
Psychological resilience	18.46	4.71	6.00	30.00
Pittsburgh Sleep Quality Index	7.22	3.51	0.00	19.00
Average nightly sleep duration, hours	6.71	1.19	3.10	10.20
Sleep-onset latency, minutes	28.64	21.73	2.00	120.00
Weekly moderate-to-vigorous physical activity, minutes	147.82	104.36	0.00	540.00
Daily sedentary time, hours	7.46	2.21	2.00	14.00
Daily non-essential screen time, hours	4.18	2.03	0.50	11.50
Perceived social support	58.37	13.42	18.00	84.00
Perceived financial strain	4.29	2.11	1.00	10.00
Meaningful social interactions per week	4.84	2.76	0.00	15.00

As shown in Table 1, the study variables demonstrated sufficient dispersion to support multivariable predictive modeling. The mean perceived stress score was 18.92 ($SD = 6.54$), whereas the mean generalized anxiety symptom score was 7.41 ($SD = 5.37$), indicating that a considerable proportion of participants experienced at least mild levels of stress and anxiety. Mean self-esteem was 27.68 ($SD = 5.42$), while loneliness averaged 7.83 ($SD = 3.08$) and psychological resilience averaged 18.46 ($SD = 4.71$). Sleep-

related indicators suggested that sleep difficulties were relatively common in the sample. The mean Pittsburgh Sleep Quality Index score was 7.22 ($SD = 3.51$), exceeding the conventional threshold generally associated with poor sleep quality, and participants reported an average nightly sleep duration of 6.71 hours ($SD = 1.19$). The average sleep-onset latency was 28.64 minutes ($SD = 21.73$), further indicating substantial variability in sleep initiation. With respect to lifestyle variables, participants reported an average of

147.82 minutes (SD = 104.36) of moderate-to-vigorous physical activity per week, 7.46 hours (SD = 2.21) of sedentary time per day, and 4.18 hours (SD = 2.03) of daily non-essential screen time. The mean perceived social support score was 58.37 (SD = 13.42), while the mean financial strain score was 4.29 (SD = 2.11). Participants

reported an average of 4.84 (SD = 2.76) meaningful social interactions per week. Overall, these descriptive findings indicated considerable heterogeneity across psychological, behavioral, sleep-related, and social characteristics, thereby providing an appropriate multidimensional predictor space for the subsequent deep neural network model.

Table 2

Comparison of Study Variables Between Participants at Lower and Elevated Depression Risk

Variable	Lower Risk (n = 670), M ± SD	Elevated Risk (n = 372), M ± SD	t	p	Cohen's d
Perceived stress	15.72 ± 5.18	24.68 ± 4.89	-27.22	< .001	1.76
Generalized anxiety symptoms	4.67 ± 3.73	12.34 ± 4.16	-29.55	< .001	1.97
Self-esteem	30.11 ± 4.43	23.30 ± 4.12	24.45	< .001	1.57
Loneliness	6.58 ± 2.42	10.08 ± 2.71	-20.77	< .001	1.39
Psychological resilience	20.12 ± 4.11	15.47 ± 4.11	17.44	< .001	1.13
Sleep quality score	5.83 ± 2.73	9.73 ± 3.24	-19.72	< .001	1.34
Nightly sleep duration, hours	7.06 ± 1.04	6.08 ± 1.18	13.33	< .001	0.90
Sleep-onset latency, minutes	22.18 ± 16.47	40.27 ± 25.08	-12.43	< .001	0.91
Weekly physical activity, minutes	172.31 ± 107.42	103.72 ± 82.16	11.57	< .001	0.69
Daily sedentary time, hours	6.83 ± 1.97	8.59 ± 2.17	-12.98	< .001	0.86
Daily screen time, hours	3.64 ± 1.72	5.15 ± 2.18	-11.48	< .001	0.80
Perceived social support	64.36 ± 10.91	47.58 ± 10.86	23.80	< .001	1.54
Financial strain	3.49 ± 1.73	5.73 ± 1.91	-18.74	< .001	1.25
Meaningful social interactions per week	5.72 ± 2.53	3.25 ± 2.38	15.67	< .001	1.00

Table 2 presents the unadjusted differences in the principal predictive variables between participants classified as being at lower versus elevated depression risk. Statistically significant differences were observed across all examined domains. Participants in the elevated-risk group reported markedly greater perceived stress than those in the lower-risk group, with means of 24.68 and 15.72, respectively, $t = -27.22$, $p < .001$, Cohen's $d = 1.76$. A similarly pronounced difference was observed for generalized anxiety symptoms, with the elevated-risk group reporting a mean score of 12.34 compared with 4.67 among lower-risk participants, $t = -29.55$, $p < .001$, $d = 1.97$. Elevated-risk participants also demonstrated substantially lower self-esteem and psychological resilience and substantially higher loneliness. In particular, perceived social support differed strongly between groups, with a mean of 47.58 in the elevated-risk group and 64.36 in the lower-risk group, $t = 23.80$, $p < .001$, $d = 1.54$. Sleep variables were

also clearly differentiated by depression-risk status. Participants at elevated risk reported poorer overall sleep quality, shorter nightly sleep duration, and longer sleep-onset latency. Lifestyle differences showed a similar pattern, as elevated-risk participants engaged in fewer weekly minutes of moderate-to-vigorous physical activity while reporting higher daily sedentary time and screen exposure. Financial strain was considerably greater among participants at elevated depression risk, whereas the frequency of meaningful social interactions was lower. Effect sizes were particularly large for anxiety, stress, self-esteem, social support, loneliness, sleep quality, and financial strain. Although these group comparisons were not intended to establish causal relationships or determine independent predictor importance, they demonstrated that depression-risk status was associated with a broad and coherent pattern of psychological vulnerability, sleep disturbance, behavioral disadvantage, and reduced social resources.

Table 3

Predictive Performance of the Deep Neural Network and Benchmark Models in the Independent Test Sample

Model	Accuracy	Sensitivity	Specificity	Precision	F1 Score	ROC-AUC	PR-AUC	Brier Score
Deep neural network	0.87	0.84	0.89	0.82	0.83	0.93	0.89	0.101
Logistic regression	0.81	0.76	0.84	0.73	0.74	0.87	0.80	0.142
Random forest	0.84	0.78	0.87	0.78	0.78	0.90	0.84	0.125
Gradient boosting classifier	0.85	0.81	0.87	0.79	0.80	0.91	0.86	0.116

The performance indices shown in Table 3 indicated that the deep neural network achieved the strongest overall predictive performance in the independent test sample. The neural network correctly classified 87% of participants and achieved a sensitivity of 0.84, indicating that 84% of participants who met the criterion for elevated depression risk were correctly identified by the model. Specificity was 0.89, demonstrating that the model also maintained a relatively low false-positive rate among participants classified as being at lower risk. Precision was 0.82 and the F1 score was 0.83, indicating a favorable balance between identification of true elevated-risk cases and control of false-positive predictions. The receiver operating characteristic area under the curve was 0.93, representing excellent discrimination between participants with and without elevated depression risk. The precision-recall area under the

curve was 0.89, which was particularly relevant given that elevated-risk participants constituted approximately one third of the sample. The Brier score of 0.101 suggested satisfactory probabilistic accuracy and calibration. In comparison, logistic regression produced a ROC-AUC of 0.87 and an accuracy of 0.81, while the random forest achieved a ROC-AUC of 0.90 and an accuracy of 0.84. Gradient boosting yielded stronger performance than logistic regression and random forest but remained below the deep neural network, with an accuracy of 0.85 and ROC-AUC of 0.91. The improvement in both discrimination and balanced classification performance indicated that the deep neural network was able to capture nonlinear and potentially interactive relationships among psychological, sleep-related, lifestyle, and social variables that were not fully represented by the conventional benchmark models.

Table 4

Relative Importance of Predictors Based on Mean Absolute SHAP Values in the Final Deep Neural Network

Rank	Predictor	Mean Absolute SHAP Value	Direction Associated With Higher Predicted Risk
1	Generalized anxiety symptoms	0.184	Higher
2	Perceived stress	0.167	Higher
3	Perceived social support	0.139	Lower support
4	Self-esteem	0.126	Lower self-esteem
5	Loneliness	0.118	Higher
6	Sleep quality score	0.106	Poorer sleep quality
7	Financial strain	0.091	Higher
8	Psychological resilience	0.081	Lower resilience
9	Nightly sleep duration	0.069	Shorter duration
10	Daily sedentary time	0.061	Higher
11	Daily screen time	0.054	Higher
12	Weekly physical activity	0.048	Lower activity
13	Meaningful social interactions	0.043	Fewer interactions
14	Sleep-onset latency	0.037	Longer latency
15	Employment status	0.024	Unemployment/instability
16	Household income category	0.021	Lower income
17	Relationship status	0.018	Single/no partner
18	Age	0.013	Younger age
19	Student status	0.010	Variable contribution
20	Urban/rural residence	0.006	Minimal contribution

Figure 1

Receiver Operating Characteristic Curve of the Deep Neural Network for Predicting Elevated Depression Risk in the Independent Test Sample

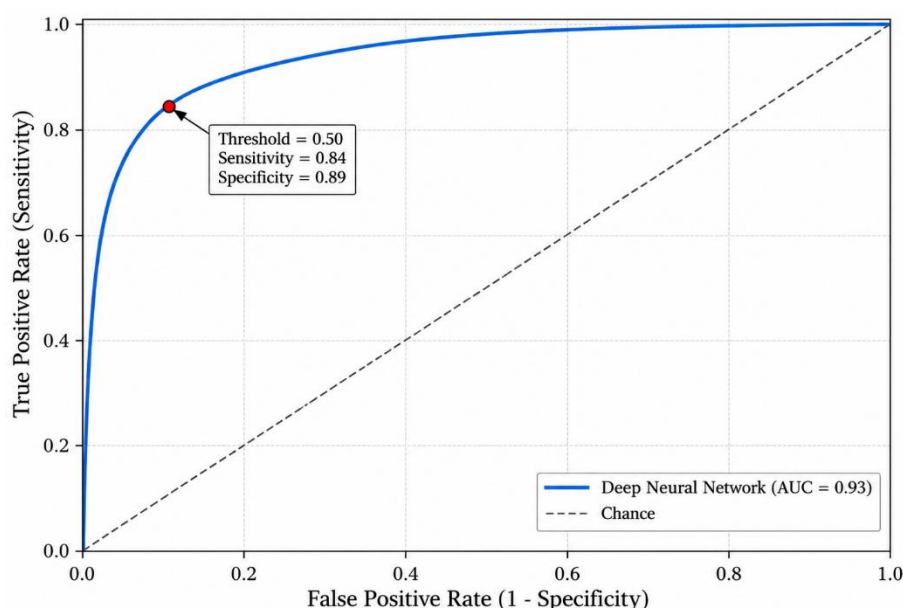


Table 4 presents the relative importance of the predictors in the final deep neural network based on mean absolute SHAP values. Generalized anxiety symptoms emerged as the most influential predictor of depression risk, with a mean absolute SHAP value of 0.184, followed by perceived stress at 0.167. Higher anxiety and stress scores consistently shifted model predictions toward a greater probability of elevated depression risk. Social and self-evaluative variables also played a prominent role. Lower perceived social support was the third most influential predictor, followed by lower self-esteem and greater loneliness. Poor sleep quality ranked sixth and showed a clear positive contribution to predicted risk, whereas greater financial strain ranked seventh. Lower psychological resilience, shorter nightly sleep duration, and greater sedentary time completed the 10 strongest predictors. Lifestyle characteristics such as higher daily screen time and lower weekly physical activity made smaller but still meaningful contributions to model predictions. Fewer meaningful social interactions and longer sleep-onset latency also increased predicted risk, although their average contributions were less substantial than those of the leading psychological variables. Demographic and contextual predictors, including employment status, household income, relationship status, age, student status, and urban-rural residence, contributed comparatively little after the more proximal psychological, sleep, lifestyle, and social characteristics had been incorporated into the network.

These findings suggested that the predictive performance of the neural network was driven predominantly by modifiable or potentially modifiable psychosocial and behavioral factors rather than by static demographic characteristics.

The receiver operating characteristic curve shown in Figure 1 further illustrated the discriminative ability of the deep neural network. The curve remained substantially above the diagonal line representing chance-level classification across a wide range of decision thresholds, corresponding to an ROC-AUC of 0.93. This result indicated a 93% probability that, when one participant at elevated depression risk and one participant at lower risk were randomly selected from the test sample, the model would assign a higher predicted probability to the elevated-risk participant. At the conventional classification threshold of 0.50, the model provided a sensitivity of 0.84 and specificity of 0.89. Examination of alternative thresholds showed that lowering the classification threshold increased sensitivity at the cost of additional false-positive classifications, whereas raising the threshold improved specificity while reducing case detection. Because the intended use of the model was risk identification rather than clinical diagnosis, the observed discrimination suggested that the network could support screening-oriented applications in which relatively high sensitivity is desirable. Importantly, the performance illustrated in the ROC analysis was obtained exclusively from the independent test dataset that had not been used for

model fitting or hyperparameter selection, thereby providing a more conservative indication of out-of-sample generalization than training or validation performance alone.

4. Discussion

The present study developed and evaluated a deep neural network model for predicting elevated depression risk among 1,042 young adults in Canada using psychological, sleep-related, lifestyle, and social variables. The model demonstrated strong predictive performance in the independent test sample, achieving an accuracy of 0.87, sensitivity of 0.84, specificity of 0.89, an F1 score of 0.83, and a ROC-AUC of 0.93. These findings indicate that depression risk among young adults can be estimated with a high degree of discrimination when multiple domains of functioning are considered simultaneously. The deep neural network also outperformed logistic regression, random forest, and gradient boosting, suggesting that nonlinear and interactive relationships among the predictors contained information that was not fully captured by more conventional statistical and machine-learning approaches. The most influential predictors were generalized anxiety symptoms, perceived stress, perceived social support, self-esteem, loneliness, sleep quality, financial strain, psychological resilience, sleep duration, and sedentary time. Taken together, the findings support a multidimensional conceptualization of depression risk in young adulthood, in which psychological distress is embedded within broader patterns of sleep disturbance, lifestyle behavior, and social conditions rather than operating in isolation.

Generalized anxiety symptoms emerged as the strongest predictor of elevated depression risk, followed by perceived stress. This result is consistent with evidence demonstrating substantial overlap between anxiety and depressive symptomatology among young adults and university students. Anxiety and depression often co-occur and may share cognitive, affective, and physiological mechanisms, including persistent negative affect, rumination, autonomic arousal, impaired emotion regulation, and heightened sensitivity to stress. Wen et al. demonstrated strong associations between anxiety and depression among college students and identified interconnected pathways through which these forms of psychological distress may reinforce one another (Wen et al., 2022). The current findings extend this evidence by showing that anxiety and stress remained the most influential variables even when sleep, social, lifestyle, and demographic indicators were included in a

nonlinear predictive model. This suggests that anxiety and stress are not merely correlates of depressive symptoms but are central components of the multidimensional risk profile captured by the neural network.

The strong contribution of perceived stress is also compatible with the broader literature on mental health among students and young adults. Young adulthood frequently involves academic pressure, unstable employment, financial uncertainty, relationship changes, and transitions in living arrangements, all of which may increase cumulative psychological strain. Studies conducted in university populations have highlighted the substantial mental health burden associated with such pressures, particularly following periods of social and educational disruption (Patrono et al., 2022; Ray, 2023). The present findings suggest that perceived stress may function as a central node linking external demands with depressive vulnerability. This interpretation is also consistent with the observed interaction patterns, in which high stress was especially strongly associated with predicted depression risk when accompanied by high anxiety or low social support. Such findings support the idea that stress becomes more consequential when protective psychological and social resources are limited.

Perceived social support was the third most influential predictor and showed a strong inverse relationship with depression risk. Participants at elevated risk had substantially lower social support than those in the lower-risk group, and SHAP analyses indicated that reduced support consistently shifted model predictions toward greater risk. This result aligns with research emphasizing the importance of social connection and interpersonal resources for psychological adjustment. Philbrook et al. found that loneliness was associated with poorer adjustment in young adults and that sleep quality could operate as a protective factor within this relationship (Philbrook et al., 2023). Similarly, social capital has been associated with sleep duration and broader health-related outcomes, illustrating the interconnectedness of social resources and behavioral health (Nutakor et al., 2023). Although the latter study focused on an older population, the broader implication that social integration can influence health behavior is relevant to the current findings. In young adults, adequate social support may reduce perceived stress, promote more stable routines, provide emotional regulation resources, and buffer the effects of loneliness and financial difficulties.

Loneliness itself ranked among the most important predictors and was substantially higher among participants

at elevated depression risk. This finding is particularly important because loneliness is not simply the absence of social contact but reflects dissatisfaction with the quality or adequacy of social connection. Young adults can therefore experience loneliness even in the presence of frequent digital communication or large social networks. The protective role of high-quality social connection is supported by previous evidence showing that loneliness is closely associated with maladjustment in young adulthood (Philbrook et al., 2023). The present study further suggests that loneliness interacts with other vulnerability domains. Poor sleep quality, for example, contributed more strongly to predicted depression risk among participants who also reported high loneliness. This pattern is theoretically plausible because social disconnection may increase cognitive arousal and rumination, which may interfere with sleep, while poor sleep may in turn reduce emotional regulation and interpersonal functioning.

Self-esteem and psychological resilience also emerged as important protective predictors. Participants at elevated depression risk reported markedly lower self-esteem and resilience, and lower values on both variables increased the model-estimated probability of depression. These findings are consistent with a broader understanding of depression risk as reflecting not only exposure to adverse factors but also the availability of internal psychological resources. Positive psychological characteristics may help individuals interpret stressful events in less threatening ways, recover more effectively from adversity, maintain social engagement, and preserve healthier daily routines. Related research has suggested that positive psychological orientations such as gratitude may be associated with better sleep quality among young adults (Narang, 2024). The current results extend this general pattern by indicating that psychological resources operate alongside social and behavioral factors in shaping depression risk.

Sleep quality was the most influential sleep-related predictor and ranked sixth overall. Participants at elevated depression risk had substantially poorer sleep quality, shorter sleep duration, and longer sleep-onset latency than those at lower risk. These findings are highly consistent with the literature linking sleep disturbance with mental health problems in adolescents, university students, and young adults. Kim et al. reported meaningful associations between sleep characteristics and mental health among university students (Kim et al., 2022), while Uccella et al. emphasized the implications of insomnia and sleep deprivation for mental health during adolescence and the transition to

adulthood (Uccella et al., 2023). Psychological factors have also been shown to influence sleep quality among university students, supporting a reciprocal relationship in which distress worsens sleep and disrupted sleep subsequently intensifies emotional difficulties (Anandavelu et al., 2022). The present results reinforce this reciprocal model by demonstrating that sleep characteristics retained predictive importance even after psychological variables such as anxiety and stress were simultaneously considered.

The importance of sleep duration also deserves attention. Shorter nightly sleep was associated with greater predicted depression risk, and the SHAP dependence analysis suggested a nonlinear pattern in which risk was lowest around seven to eight hours of sleep and increased more sharply at shorter durations. This finding is compatible with evidence showing that insufficient sleep can contribute to a wide range of cognitive and emotional impairments. Xu et al. demonstrated that sleep is associated with multimodal cognitive functioning among college students (Xu et al., 2025), and Hua et al. found that depression and insufficient sleep jointly contributed to self-harm behaviors among college students (Hua et al., 2023). These findings indicate that insufficient sleep may amplify the consequences of existing psychological vulnerability. From a predictive perspective, sleep duration may therefore function not only as an independent risk indicator but also as a contextual variable that modifies the effects of stress, anxiety, and social disadvantage.

Circadian and sleep-timing mechanisms provide an additional explanation for the observed importance of sleep variables. Young adults frequently experience delayed sleep schedules, irregular bedtimes, and misalignment between biological preferences and educational or occupational demands. Delayed sleep-wake phase disorder has been identified as a meaningful problem among university students and young adults (Sivertsen et al., 2021), and related work has documented behavioral characteristics associated with delayed sleep-wake patterns in younger populations (Futenma et al., 2023). Chronotype has also been associated with depression risk, with eveningness frequently linked to greater vulnerability (Zhao et al., 2025). More broadly, circadian disruption has been implicated in several psychiatric conditions (Zou et al., 2022), while circadian management has been proposed as an important component of mental health promotion among college students (Yeom & Lee, 2024). The present findings are consistent with this literature because sleep quality, sleep duration, and sleep-onset latency all contributed to the

predictive model, suggesting that depression risk may partly reflect instability in both sleep amount and temporal organization.

Lifestyle-related predictors also contributed meaningfully to model performance. Participants at elevated depression risk reported lower weekly physical activity, greater sedentary time, and longer daily screen exposure. Sedentary time and screen time both appeared among the higher-ranked lifestyle predictors, while lower physical activity also increased predicted risk. These findings are consistent with current lifestyle medicine perspectives, which emphasize physical activity, sleep, stress regulation, social connection, and related behaviors as important elements in the prevention and management of major depressive disorder (Merlo et al., 2026). Exercise has also been shown to support sleep health in college students through physiological and psychological mechanisms (Chen et al., 2025). Accordingly, physical activity may influence depression risk both directly through mood-related mechanisms and indirectly through improved sleep, circadian regulation, and stress reduction.

The contribution of screen exposure is also supported by evidence concerning digital behavior and sleep. Excessive electronic device use among young people has been associated with delayed sleep timing, reduced sleep duration, and poorer sleep quality (Sysło et al., 2024). Digital addiction has likewise been linked to sleep disruption (Dresp & Hutt, 2022). These relationships may help explain why screen time contributed to depression prediction in the present study even though it ranked below more proximal psychological factors. Excessive digital exposure may increase depression risk indirectly by displacing sleep, physical activity, face-to-face social interaction, and outdoor activity. It may also contribute to cognitive stimulation and emotional arousal close to bedtime, which can increase sleep-onset latency. Bedtime routines and strategies for initiating sleep have been shown to vary widely in college students and may influence sleep onset and sleep quality (Meneo et al., 2024). Thus, the observed associations among screen time, sleep disturbance, and depression risk are likely to reflect interacting behavioral mechanisms rather than isolated effects.

Time spent outdoors and broader environmental routines may also be relevant to these lifestyle pathways. Schamilow et al. found that outdoor time was associated with sleep, optimism, happiness, and general health (Schamilow et al., 2023). Outdoor exposure may promote physical activity, social engagement, and circadian synchronization through

natural light, all of which could support mental health. In the same way, chronotype and sleep patterns have been associated with other health behaviors, including eating-related risk among university students (Tomás Olivo Martins de et al., 2024). These findings support the broader interpretation that lifestyle variables operate in clusters and that their relationship with depression is unlikely to be purely linear. The superior performance of the deep neural network may partly reflect its capacity to detect such interdependencies.

Financial strain also emerged as a relatively strong predictor. Participants at elevated depression risk reported substantially greater financial strain, and its contribution was more pronounced among individuals with low social support. Financial pressure can increase chronic stress, restrict access to healthy food and recreational activities, disrupt housing stability, and contribute to uncertainty regarding education and employment. In young adults, such pressures may be particularly salient because many individuals are simultaneously managing tuition, early career instability, and transitions toward financial independence. The importance of financial strain is consistent with evidence describing the broader mental health burden experienced by university students and young adults in periods of social and economic uncertainty (Patrono et al., 2022; Purnawati et al., 2022). The interaction observed between financial strain and social support suggests that social resources may partly buffer the psychological impact of economic difficulty.

The overall predictive superiority of the deep neural network is also noteworthy. The network achieved a ROC-AUC of 0.93 compared with 0.87 for logistic regression, 0.90 for random forest, and 0.91 for gradient boosting. This pattern suggests that depression risk in young adults may be characterized by nonlinearities, thresholds, and interactions that are incompletely represented by additive linear models. The SHAP analysis supported this interpretation. Anxiety, stress, social support, sleep duration, and sedentary behavior all showed nonlinear patterns, while stress interacted with anxiety and social support, poor sleep interacted with loneliness, and financial strain had a stronger effect in the presence of weak social support. Such patterns align with the broader literature indicating that mental health outcomes emerge from interconnected psychological, behavioral, social, and circadian systems rather than from isolated predictors (Tahmasian et al., 2026; Zou et al., 2022). The ability of deep neural networks to represent high-order

interactions may therefore offer a methodological advantage in multidomain depression-risk prediction.

The potential use of digital and sensor-derived data further strengthens the relevance of this modeling approach. Alamoudi et al. concluded that smartphone sensors may provide feasible information for tracking insomnia, depression, and anxiety in adults and young adults, although implementation challenges remain (Alamoudi et al., 2023). Combining self-reported psychological and social measures with passively collected sleep, mobility, activity, and screen-use data could improve future predictive models. Such integration may be especially useful because several of the strongest predictors identified in this study, including sleep, physical activity, sedentary behavior, and screen exposure, can potentially be measured continuously rather than retrospectively. However, interpretability and privacy remain essential considerations, particularly when predictive systems are applied in mental health contexts.

5. Conclusion

The findings also have implications for prevention. Sleep interventions in emerging adults have shown evidence of benefit, and behavior-change theory has been increasingly incorporated into such interventions (Pegado et al., 2023). Similarly, the broader lifestyle medicine literature supports interventions targeting sleep, physical activity, social connection, and stress management in the context of depression (Merlo et al., 2026). The current findings suggest that risk assessment may be most useful when it identifies patterns across several modifiable domains rather than relying exclusively on symptom scores. For example, a young adult with moderate anxiety but strong social support, adequate sleep, and high resilience may have a different risk profile from another individual with the same anxiety level but severe sleep disruption, high financial strain, and social isolation. This distinction illustrates the potential clinical value of multidimensional predictive modeling.

6. Limitations & Suggestions

Several limitations should be considered when interpreting the findings. First, the cross-sectional design does not permit causal inference, and the identified predictors should therefore be interpreted as variables associated with model-estimated depression risk rather than determinants of future depression. Second, most variables were based on self-report and may have been affected by recall bias, response style, or social desirability. Third, the

outcome was defined using a PHQ-9 threshold and therefore represented elevated depressive symptom risk rather than a clinician-confirmed diagnosis of major depressive disorder. Fourth, although the sample included young adults from Canada and incorporated a broad range of characteristics, online recruitment may have produced selection bias and may have underrepresented individuals with limited internet access or lower willingness to participate in mental health research. Fifth, the model was evaluated through an internal train-validation-test split rather than external validation in an entirely independent cohort. Consequently, the reported predictive performance may not generalize to young adults in different countries, age ranges, clinical settings, cultural groups, or socioeconomic contexts. Finally, although SHAP values improved interpretability, feature-attribution methods do not establish causality and may be influenced by correlations among predictors.

Future studies should prioritize prospective longitudinal designs in which psychological, sleep-related, behavioral, and social predictors are measured before the onset or worsening of depressive symptoms. External validation should be conducted in independent samples from different Canadian provinces, countries, cultural groups, and clinical settings to establish transportability and robustness. Researchers should also compare deep neural networks with additional contemporary algorithms and examine whether simpler models can achieve comparable performance when appropriately tuned. Incorporating objective and passively collected data from smartphones, wearable devices, actigraphy, and ecological momentary assessment could reduce reliance on retrospective self-report and provide more precise measurements of sleep duration, circadian regularity, mobility, physical activity, and digital behavior. Future models should also evaluate temporal prediction, repeated risk estimation, subgroup fairness, calibration stability, and potential differences by sex, gender, socioeconomic status, student status, and migration background. Particular attention should be given to identifying clinically meaningful combinations of modifiable factors and to determining whether changes in these predictors over time correspond to changes in depression risk.

In practice, the findings support the use of multidimensional screening approaches for young adults rather than relying exclusively on depressive symptom questionnaires. Screening programs in universities, colleges, primary care settings, community mental health services, and digital health platforms could incorporate brief

assessments of anxiety, perceived stress, social support, loneliness, sleep quality, sleep duration, physical activity, sedentary behavior, screen exposure, resilience, and financial strain. Individuals showing clusters of vulnerability across several domains may benefit from earlier assessment even when depressive symptoms have not yet reached severe levels. Interventions should prioritize modifiable factors, including stress management, anxiety reduction, sleep regularity, physical activity, reduction of excessive sedentary and screen time, strengthening of social support, and referral for financial or social services when relevant. Any predictive system used in practice should function as a decision-support or screening tool rather than as a diagnostic substitute, and predicted probabilities should be interpreted alongside clinical judgment, direct assessment, and the individual's broader psychosocial context.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

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

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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Authors' Contributions

All authors equally contributed to this article.

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