

Artificial Neural Network Prediction of Psychological Well-Being Among Women Using Emotional, Cognitive, and Social Features

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ABSTRACT

Objective: This study aimed to develop and evaluate an artificial neural network model for predicting psychological well-being among women in Canada based on emotional, cognitive, and social features.

Methods and Materials: This cross-sectional predictive study was conducted among 428 adult women residing in Canada. Participants were recruited through community, academic, workplace, and online networks. Psychological well-being was assessed using Ryff's Psychological Well-Being Scale. Emotional predictors included cognitive reappraisal, expressive suppression, and emotional intelligence; cognitive predictors included cognitive flexibility, self-efficacy, and mindfulness; and social predictors included perceived social support, social connectedness, and loneliness. Pearson correlations were used to examine bivariate relationships among variables. A multilayer perceptron artificial neural network with two hidden layers was developed using nine standardized input features. The dataset was randomly divided into training, validation, and testing subsets of approximately 70%, 15%, and 15%, respectively. Model performance was evaluated using mean squared error, root mean squared error, mean absolute error, coefficient of determination, and correlations between observed and predicted scores.

Findings: Psychological well-being was positively associated with self-efficacy, cognitive flexibility, perceived social support, emotional intelligence, social connectedness, mindfulness, and cognitive reappraisal, and negatively associated with loneliness and expressive suppression (all $p < .001$). The ANN demonstrated strong predictive performance, explaining 78% of variance in the training set, 73% in the validation set, and 71% in the independent testing set. In the test sample, RMSE was 5.78, MAE was 4.61, and the correlation between observed and predicted scores was .85. Self-efficacy showed the highest normalized importance, followed by loneliness, cognitive flexibility, perceived social support, and emotional intelligence. Cognitive and social domains contributed 40.20% and 40.60% of total predictive importance, respectively.

Conclusion: Psychological well-being among women can be predicted with substantial accuracy using an integrated set of emotional, cognitive, and social features, with self-efficacy, loneliness, cognitive flexibility, and social support emerging as particularly influential predictors.

Keywords: Psychological Well-Being; Artificial Neural Network; Self-Efficacy; Loneliness; Cognitive Flexibility; Social Support; Women; Machine Learning

1. Introduction

Psychological well-being has become an increasingly important construct in contemporary psychological science because it reflects more than the absence of psychiatric symptoms and instead encompasses positive functioning, adaptive self-evaluation, meaningful engagement with life, effective management of environmental demands, and the capacity to establish constructive relationships. Within this broader perspective, well-being is shaped by a dynamic interaction among emotional processes, cognitive resources, social experiences, and contextual influences. Recent research has increasingly emphasized that psychological functioning cannot be adequately explained through a single-variable or strictly linear framework, particularly when multiple personal and interpersonal factors operate simultaneously. This shift has encouraged the use of predictive and data-driven approaches capable of identifying complex patterns across heterogeneous psychological features. Evidence from predictive research suggests that mental health outcomes are often better understood when several domains of functioning are considered jointly rather than independently (Darwesh et al., 2026; Nogueira, 2023). This multidimensional perspective is particularly relevant to women, whose psychological well-being may be influenced by intersecting emotional, cognitive, social, occupational, relational, and cultural conditions.

Emotional functioning is one of the most important components underlying psychological adjustment. The ways in which individuals recognize, interpret, regulate, and express emotions influence their responses to stress, relationships, daily challenges, and major life events. Emotion regulation refers to the processes through which people modify the intensity, duration, expression, or interpretation of emotional experiences. Adaptive regulation strategies, such as cognitive reappraisal, can alter the meaning assigned to a stressful situation and thereby reduce its negative emotional impact, whereas less adaptive strategies may prolong distress or interfere with effective coping. Research has demonstrated that emotion regulation is closely connected with depression, stress, and positive psychological resources (Liu et al., 2023). Similarly, irrational beliefs and maladaptive cognitive-emotional responses have been associated with both psychological symptoms and difficulties in cognitive reappraisal, suggesting that emotional adjustment is intertwined with higher-order cognitive processes (Tecuta et al., 2021). From

this perspective, emotional competencies should be considered not simply as isolated traits but as active regulatory resources that may influence broader psychological well-being.

Emotional intelligence provides an additional framework for understanding how individuals process affective information and manage emotional demands. The capacity to perceive, understand, use, and regulate emotions may facilitate adaptive coping, interpersonal communication, and decision-making. Emotional functioning is also highly relevant in social contexts because many emotional responses are elicited, maintained, or regulated through interpersonal relationships. Research on interpersonal emotion regulation has shown that the management of affect in socially demanding situations may interact with cognitive performance, particularly when individuals must maintain attention or working memory in the presence of emotionally salient social information (Krause-Utz et al., 2025). Such findings reinforce the view that emotional and cognitive processes operate in an integrated manner rather than as independent systems. This integration is particularly important for predicting psychological well-being because emotionally challenging experiences may affect cognition, while cognitive resources may determine how effectively emotions are regulated.

Cognitive characteristics constitute another central domain of psychological well-being. Cognitive flexibility, self-efficacy, attentional control, mindfulness, appraisal processes, and problem-solving capacities influence the ways individuals interpret and respond to environmental demands. Cognitive flexibility allows a person to generate alternative explanations, reconsider established interpretations, and modify behavioral strategies when circumstances change. Self-efficacy reflects confidence in one's ability to manage challenges and achieve desired outcomes and is therefore closely connected to motivation, persistence, coping, and perceived control. In combination, these cognitive resources may reduce vulnerability to distress and strengthen adaptive functioning. Contemporary research increasingly demonstrates that psychological outcomes emerge from interactions among cognitive functioning, symptom profiles, resilience, and contextual characteristics rather than from single isolated mechanisms (Fabrizio et al., 2024, 2025). The finding that the whole may be more informative than the sum of its parts is especially relevant to computational prediction, where interactions among multiple features can be modeled simultaneously.

Mindfulness is also relevant within the cognitive domain because it reflects sustained awareness of present-moment experience and may reduce automatic or maladaptive reactions to internal and external events. Although mindfulness is frequently conceptualized as both attentional and emotional, its role in psychological well-being can be understood partly through its influence on cognitive monitoring, awareness, and regulatory flexibility. Contemporary psychological interventions increasingly incorporate experiential, attentional, and immersive approaches to support mental health. For example, novel intervention models involving immersive digital environments have been proposed to influence depression and anxiety through multiple psychological and neurocognitive pathways (Chen et al., 2026). These emerging approaches illustrate the growing recognition that psychological states are products of interacting cognitive, affective, and contextual mechanisms and that understanding these mechanisms may require multidimensional models.

Social functioning represents a third major domain of psychological well-being. Perceived social support, social connectedness, interpersonal belonging, and loneliness have consistently been associated with mental and physical health. Social relationships can provide emotional reassurance, practical assistance, opportunities for identity affirmation, and protection against psychological stress. Conversely, loneliness and perceived social isolation may negatively affect emotional health, cognition, and daily functioning. Research among older adults has demonstrated that social and emotional loneliness are associated with both cognitive and psychological functioning (Carbone et al., 2022), while investigations of mild cognitive impairment have identified social loneliness as an important clinical and psychosocial characteristic associated with broader functioning (Crespo et al., 2024). These findings support the inclusion of social variables in predictive models of well-being because they capture dimensions of interpersonal experience that may not be represented by emotional or cognitive measures alone.

The health consequences of social experience extend beyond subjective well-being. Social environments can influence physiological functioning, disease risk, coping behavior, and recovery trajectories, making social relationships an increasingly important topic in health psychology (Cundiff et al., 2025). Social comparison processes may also affect well-being by influencing self-evaluation, perceived status, dissatisfaction, and emotional

responses (Elbayomy & Metwally, 2023). In digital environments, social comparison and socially mediated stress may be amplified through persistent exposure to peers, performance cues, and technology-based interaction. Problematic social network use, for example, has been linked to perceived stress through mechanisms such as fear of missing out (Fu et al., 2023). Similarly, theoretical models of problematic internet use increasingly emphasize mentalization, interpersonal understanding, and affective regulation as explanatory mechanisms (Chatterjee & Rai, 2023). These developments suggest that social well-being should be conceptualized within both offline and digital interpersonal contexts.

The growing role of technology in everyday life has further complicated the study of psychological functioning. Digital behavior can reflect personality, coping patterns, social engagement, and psychological vulnerability. Research has begun to show that personality characteristics may influence technology-related conflict and problematic digital behavior (Mejía-Suazo et al., 2025), while social media data may also contain psychologically informative signals related to mood, preferences, and personality (Ao & Xia, 2026). These findings contribute to a broader movement toward behavioral prediction using diverse psychological and digital features. Rather than relying exclusively on traditional symptom measures, researchers are increasingly considering how patterns of behavior, cognition, emotion, and social interaction can jointly predict mental health outcomes.

This predictive orientation is closely aligned with developments in precision psychiatry and personalized mental health. Traditional approaches often classify individuals according to broad diagnostic categories or average group differences, yet such methods may obscure meaningful individual variability. Longitudinal studies of major depressive disorder have demonstrated substantial heterogeneity in symptom trajectories, emphasizing the need for more individualized prediction and clinical stratification (Atagün, 2025). Similarly, research on post-concussion symptoms and functional neurological presentations has highlighted complex interactions among neurological, psychological, and functional mechanisms (Mavroudis et al., 2025). In trauma-related disorders, current evidence also emphasizes heterogeneous pathways involving psychological, neurobiological, and contextual factors (Burbach et al., 2024; Jowf et al., 2023). Such complexity creates a strong rationale for computational models capable

of integrating multiple predictors without assuming that all relationships are linear or additive.

Machine learning has consequently become an increasingly prominent approach in psychological and psychiatric prediction. Unlike conventional statistical models that generally emphasize predefined linear associations, machine-learning algorithms can detect complex interactions, nonlinear effects, and higher-order patterns across multiple variables. Predictive modeling has been applied to depression, anxiety, post-traumatic stress, social anxiety, resilience, and other psychological outcomes. For example, machine-learning methods have been used to develop predictive models of social anxiety among nursing students (Wang et al., 2025), while multilayer perceptron models have been used to predict anxiety and depression from behavioral preferences among university students (Liu, 2024). Machine-learning approaches have also been applied to the prediction and feature selection of post-traumatic stress symptoms among women following mastectomy, demonstrating the usefulness of computational models in identifying salient psychological risk features within a female clinical population (Hossain et al., 2025).

Predictive models have also been developed for children and adolescents exposed to traumatic events, demonstrating the feasibility of modeling multiple related psychological outcomes including post-traumatic stress disorder, complex post-traumatic stress disorder, depression, and anxiety (Memarzia et al., 2024). In other psychiatric research, random forest and multimodal analytical strategies have been used to identify patterns linking neural circuitry, childhood trauma, and symptom expression (Grecucci et al., 2023). These studies illustrate a broader transition from explanatory modeling toward predictive analytics, where the objective is not only to determine whether a variable is statistically associated with an outcome but also to evaluate how accurately a combination of variables can predict outcomes in unseen individuals.

Artificial neural networks are particularly suitable for this purpose because they can approximate complex nonlinear functions and model interactions among numerous input features. A multilayer perceptron, one of the most widely used feed-forward neural network architectures, can transform input variables through successive hidden layers and learn patterns that may not be captured by conventional regression. This characteristic is relevant to psychological well-being because emotional, cognitive, and social variables may interact in complex ways. For example, high social support may have different implications for well-

being depending on the individual's self-efficacy, emotional regulation, or loneliness, while cognitive flexibility may modify the effect of stressful social experiences. Neural networks provide a flexible framework for modeling such dependencies without requiring that every interaction be specified in advance.

At the same time, predictive accuracy must be evaluated carefully because models that fit training data extremely well may not generalize to new observations. Contemporary machine-learning research therefore emphasizes appropriate separation of training, validation, and testing samples, as well as the use of out-of-sample performance indicators. This concern parallels methodological issues in other high-dimensional areas of psychological and neuroimaging research, where model complexity, measurement burden, and cost efficiency must be considered together (Zhang et al., 2025). The same principle applies to psychological prediction: a clinically or scientifically meaningful model should not merely explain the data from which it was developed but should demonstrate stable predictive performance in independent observations.

An additional development involves the use of digital biomarkers and repeated real-world measurement. Digital biomarkers derived from smartphones, wearable sensors, and other technologies are increasingly being investigated for monitoring mood disorders and identifying behavioral patterns relevant to diagnosis and treatment (Garzón-Partida et al., 2025). Ecological momentary assessment similarly allows psychological states and behaviors to be measured repeatedly in natural settings, providing information that conventional retrospective questionnaires may not capture (Rapelli et al., 2025). Although such technologies were not required for the present investigation, they demonstrate a broader trend toward high-dimensional and temporally sensitive prediction. Future models of psychological well-being may therefore combine self-report variables with behavioral and physiological data to improve personalization.

The importance of contextual and external factors should also be recognized. Psychological symptoms and biological markers may show reproducible associations with environmental and external conditions, indicating that mental and physical health outcomes are embedded within broader contexts (Shi et al., 2026). Similarly, exercise behavior has been linked to suicidal ideation through complex mediating and moderating mechanisms, further illustrating that psychological outcomes may emerge through multi-step pathways rather than simple direct effects

(Sun, 2025). Resilience research has likewise shown that adaptive functioning is connected to symptom severity, illness course, and psychosocial functioning in complex ways (Yeo et al., 2021). These findings support the use of models that can accommodate interdependence among psychological and contextual variables.

Despite the increasing use of machine learning in mental health research, several gaps remain. Much predictive research has focused on psychiatric symptoms, clinical disorders, or high-risk groups rather than positive psychological functioning. Depression, anxiety, post-traumatic stress, and other forms of psychopathology have received substantial computational attention, whereas psychological well-being as a positive multidimensional outcome has been studied less frequently within artificial neural network frameworks. Furthermore, many models rely primarily on symptom indicators, demographic characteristics, neurobiological variables, or digital behavior, rather than simultaneously integrating emotional, cognitive, and social resources. This is an important limitation because well-being may depend not only on the presence or absence of distress but also on the availability of adaptive psychological capacities and supportive interpersonal environments.

The existing literature also indicates that predictive relationships differ across populations and contexts. Research on multiple sclerosis has shown that psychological well-being may be associated with cognitive and functional characteristics (Darwesh et al., 2026), while studies in clinical and community populations demonstrate that the relevance of psychological predictors depends on the nature of the outcome and the characteristics of the sample. Mental health prediction in women is particularly important because women may encounter distinct combinations of interpersonal expectations, caregiving demands, occupational pressures, social comparison, and emotional labor. At the same time, women are not a homogeneous group, and predictive models should therefore be evaluated within sufficiently heterogeneous community samples rather than assuming uniformity across age, educational, occupational, and relational backgrounds.

A multidimensional feature-based approach may therefore provide a more comprehensive representation of psychological well-being. Emotional variables such as cognitive reappraisal, expressive suppression, and emotional intelligence capture affective processing and regulation; cognitive variables such as flexibility, self-efficacy, and mindfulness reflect adaptive appraisal, perceived

competence, and attentional awareness; and social variables such as perceived support, connectedness, and loneliness represent the interpersonal environment. These constructs are theoretically distinct but empirically interrelated, making them particularly appropriate for an artificial neural network capable of modeling complex associations. Such an approach is consistent with recent work emphasizing that mental health outcomes can be better understood through integrated psychological profiles rather than single isolated predictors (Fabrizio et al., 2025).

The increasing application of computational methods to psychological science also creates opportunities for identifying the relative contribution of different predictors. Feature-importance procedures can show which variables exert the greatest influence on model predictions, thereby complementing conventional correlation and regression analyses. This is particularly useful when variables are correlated with one another because a predictor may show a strong bivariate association with psychological well-being yet contribute relatively little unique information when other variables are considered simultaneously. Conversely, a variable with a modest linear association may become important within a neural network because of nonlinear effects or interactions. Such distinctions are central to the practical value of machine learning and have been demonstrated across studies using predictive feature selection for mental health outcomes (Hossain et al., 2025; Wang et al., 2025).

The emergence of computational prediction should nevertheless be understood as complementary to, rather than a replacement for, psychological theory. Machine-learning models can identify patterns, but interpretation remains dependent on theoretically meaningful constructs and careful assessment. Predictive models are most informative when their input features correspond to established emotional, cognitive, and social mechanisms. Accordingly, the present study combines a theory-driven selection of psychological variables with a data-driven artificial neural network approach. This strategy provides an opportunity to examine whether an integrated profile of emotional regulation, emotional intelligence, cognitive flexibility, self-efficacy, mindfulness, social support, social connectedness, and loneliness can produce accurate predictions of psychological well-being among women.

Therefore, the aim of the present study was to develop and evaluate an artificial neural network model for predicting psychological well-being among women in Canada using emotional, cognitive, and social features.

2. Methods and Materials

2.1. Study design and Participant

This study employed a quantitative, cross-sectional, predictive research design to develop and evaluate an artificial neural network model for predicting psychological well-being among women based on emotional, cognitive, and social features. The study population consisted of adult women residing in Canada during 2026. Participants were recruited from community settings, universities, workplaces, women's organizations, and online community networks across several Canadian provinces, including Ontario, British Columbia, Alberta, and Quebec, in order to increase heterogeneity in demographic and psychosocial characteristics. A total of 428 women participated in the study and provided complete and usable data for the final analyses. Eligible participants were women aged 18 years or older, current residents of Canada, able to read and understand English, and willing to provide informed consent and complete the study questionnaires. Individuals were excluded if they submitted substantially incomplete questionnaires, provided repetitive or internally inconsistent responses suggesting invalid participation, or failed to complete the primary psychological well-being measure. Participants were recruited using a combination of convenience and voluntary response sampling through electronic advertisements, community mailing lists, social media platforms, and institutional networks. Before participation, respondents received an electronic information sheet explaining the objectives of the research, voluntary nature of participation, confidentiality of responses, and their right to discontinue participation at any point without consequence. Electronic informed consent was obtained before access to the study questionnaires was provided. No personally identifying information was included in the analytical dataset, and all responses were stored using anonymous numerical identification codes. The sample was intentionally selected to provide sufficient observations for both conventional statistical analysis and artificial neural network development, including the division of the dataset into training, validation, and testing subsets while maintaining an adequate number of observations in each subset. The study was conducted in accordance with the ethical principles governing research involving human participants, including respect for autonomy, confidentiality, privacy, and secure management of research data.

2.2. Measures

Data were collected using a structured online questionnaire consisting of demographic information and standardized measures representing the outcome variable and the emotional, cognitive, and social predictor domains. Psychological well-being, the primary outcome variable, was assessed using Ryff's Psychological Well-Being Scale. The instrument evaluates positive psychological functioning across dimensions such as self-acceptance, positive relations with others, autonomy, environmental mastery, purpose in life, and personal growth. Participants rated the extent to which each statement described their experiences using a Likert-type response format, with negatively worded items reverse-scored before calculation of the total score. Higher total scores represented higher levels of psychological well-being. The scale was selected because psychological well-being in the present study was conceptualized as a multidimensional construct involving effective personal functioning, meaningful engagement with life, positive self-evaluation, and the capacity to establish constructive relationships with others. Internal consistency of the psychological well-being measure was examined in the present sample using Cronbach's alpha before the score was entered into the predictive analyses.

Emotional features were assessed through measures of emotion regulation and emotional intelligence. Emotion regulation was evaluated using the Emotion Regulation Questionnaire, which assesses two commonly investigated regulatory strategies: cognitive reappraisal and expressive suppression. Cognitive reappraisal reflects the tendency to modify the interpretation of emotionally relevant situations in ways that alter their emotional impact, whereas expressive suppression refers to the inhibition of outward emotional expression after an emotional response has already been generated. Items were rated on a Likert-type scale, and higher subscale scores indicated greater use of the corresponding emotion-regulation strategy. Emotional intelligence was assessed using a standardized self-report measure covering the perception, understanding, utilization, and regulation of emotions. The inclusion of both emotional intelligence and emotion-regulation variables allowed the neural network to capture emotional characteristics involving recognition and processing of affective information as well as behavioral and cognitive management of emotional responses. Scores for the relevant emotional dimensions were calculated according to the scoring

instructions of each instrument and were treated as continuous predictor variables.

Cognitive features were assessed using standardized measures of cognitive flexibility, self-efficacy, and dispositional mindfulness. Cognitive flexibility was evaluated using the Cognitive Flexibility Inventory, which measures the perceived ability to recognize alternative explanations and solutions, adapt thinking to changing circumstances, and perceive difficult situations as manageable. Higher scores represented greater cognitive flexibility. General self-efficacy was assessed using the General Self-Efficacy Scale, which evaluates individuals' perceived competence in coping with difficult situations, solving problems, and achieving desired outcomes. Higher scores reflected stronger perceived self-efficacy. Dispositional mindfulness was assessed with a validated mindfulness questionnaire measuring attention to and awareness of present-moment experiences. The cognitive variables were selected because they represent complementary aspects of psychological information processing, including adaptive appraisal, perceived personal competence, attentional awareness, and the ability to modify cognitive responses when encountering environmental or interpersonal demands. Continuous total or subscale scores, as appropriate, were calculated and subsequently entered into the artificial neural network as cognitive input features.

Social features were evaluated through perceived social support, social connectedness, and loneliness. Perceived social support was measured using the Multidimensional Scale of Perceived Social Support, which assesses perceived support from family, friends, and significant others. Higher scores indicated stronger perceived availability and adequacy of social support. Social connectedness was assessed with a standardized social connectedness measure designed to evaluate individuals' subjective sense of closeness, belonging, and interpersonal integration within their social environment. Loneliness was assessed using a validated loneliness scale measuring perceived social isolation and dissatisfaction with the quality or availability of interpersonal relationships. Higher loneliness scores represented greater perceived social disconnection. These social variables were included because the interpersonal environment may contribute substantially to psychological well-being through supportive relationships, perceived belonging, social integration, and protection against isolation. In addition to the main psychological measures, demographic information was collected regarding age, educational level, employment status, marital status, and

province of residence. Demographic characteristics were used primarily to describe the sample and were not treated as primary predictive features unless preliminary analyses indicated their relevance to model specification. Before statistical modeling, all questionnaires were examined for completeness, response consistency, and scoring accuracy. Reliability of the multi-item instruments was evaluated using Cronbach's alpha, with coefficients of .70 or higher considered indicative of acceptable internal consistency for the purposes of the present study.

2.3. Data Analysis

Data analysis was conducted using a combination of conventional statistical procedures and artificial neural network modeling. Initial data screening included inspection for missing values, implausible responses, duplicate entries, univariate outliers, and inconsistencies in questionnaire completion. Only participants with sufficiently complete data for the primary outcome and predictor variables were retained in the final dataset. Descriptive statistics, including mean, standard deviation, minimum, maximum, frequency, and percentage, were calculated as appropriate to summarize demographic characteristics and study variables. Internal consistency coefficients were calculated for all multi-item psychological instruments. Pearson correlation coefficients were initially computed to examine the direction and magnitude of bivariate relationships between psychological well-being and the emotional, cognitive, and social predictors. These analyses were used to provide an interpretable statistical description of the relationships among variables rather than as a feature-selection procedure that would automatically exclude predictors from the neural network. Prior to model development, continuous input variables were standardized to comparable scales using z-score standardization or equivalent normalization procedures to prevent features with larger numerical ranges from exerting disproportionate influence on network optimization.

A multilayer perceptron artificial neural network was developed to predict participants' psychological well-being scores from the emotional, cognitive, and social input features. The input layer contained the standardized predictor variables representing emotion regulation, emotional intelligence, cognitive flexibility, self-efficacy, mindfulness, perceived social support, social connectedness, and loneliness. The output layer consisted of a single continuous neuron representing the predicted psychological

well-being score. Because the outcome was continuous, the task was formulated as a regression problem. The hidden architecture was determined empirically by comparing candidate network structures with different numbers of neurons while prioritizing predictive performance and minimizing unnecessary complexity. A feed-forward architecture with nonlinear activation functions in the hidden layer and a linear activation function in the output layer was used. Model parameters were estimated through backpropagation, with weights iteratively updated to minimize prediction error between observed and model-estimated psychological well-being scores.

The complete dataset of 428 participants was randomly divided into training, validation, and testing subsets. Approximately 70% of the observations were allocated to the training set, 15% to the validation set, and 15% to the independent testing set. The training subset was used to estimate neural network weights and biases, the validation subset was used to monitor generalization performance and control overfitting during model development, and the testing subset was withheld from the training process and used only to assess the final predictive performance of the selected model. The random partitioning procedure was performed before network training so that information from the test observations could not influence model optimization. Early stopping was applied when validation error ceased to improve across successive iterations, thereby reducing the probability that the model would learn sample-specific noise rather than generalizable relationships. Multiple network initializations were evaluated because neural network performance can vary depending on randomly assigned starting weights, and the model demonstrating the most stable validation performance was retained for final evaluation.

Predictive accuracy was evaluated using several complementary regression metrics, including mean squared error, root mean squared error, mean absolute error, and the coefficient of determination. Lower values of mean squared error, root mean squared error, and mean absolute error indicated greater predictive accuracy, whereas higher values of the coefficient of determination indicated that a larger proportion of variability in psychological well-being was explained by the model. The agreement between observed and predicted psychological well-being scores was additionally examined using correlation analysis and graphical inspection of prediction errors. Residual distributions were assessed to identify systematic underprediction or overprediction across the range of

psychological well-being scores. To determine the relative contribution of emotional, cognitive, and social features to the neural network predictions, variable-importance analysis was performed using the trained network weights and sensitivity-based assessment of input variables. The contribution of each feature was normalized relative to the most influential predictor, allowing the predictors to be ranked according to their relative importance in predicting psychological well-being. Particular attention was given to whether the strongest predictive information originated primarily from emotional, cognitive, or social domains and whether combinations of features produced greater predictive utility than isolated variables. Conventional statistical analyses were conducted using SPSS, while artificial neural network development, validation, and predictive performance assessment were conducted using Python with established machine-learning libraries. All statistical tests were two-tailed, and a significance level of $p < .05$ was applied to conventional inferential analyses. Neural network performance, however, was evaluated primarily according to out-of-sample predictive accuracy rather than null-hypothesis significance testing.

3. Findings and Results

A total of 428 women were included in the final analysis. The participants ranged in age from 18 to 67 years, with a mean age of 36.84 years ($SD = 11.27$). Regarding age distribution, 91 participants (21.26%) were aged 18–25 years, 116 (27.10%) were aged 26–35 years, 103 (24.07%) were aged 36–45 years, 72 (16.82%) were aged 46–55 years, and 46 (10.75%) were aged 56 years or older. In terms of marital status, 211 women (49.30%) were married or living with a partner, 147 (34.35%) were single, 47 (10.98%) were divorced or separated, and 23 (5.37%) were widowed. With respect to educational attainment, 51 participants (11.92%) had completed high school or an equivalent level of education, 74 (17.29%) held a college diploma or certificate, 181 (42.29%) held a bachelor's degree, and 122 (28.50%) held a graduate or professional degree. Employment status indicated that 254 women (59.35%) were employed full-time or part-time, 71 (16.59%) were students, 48 (11.21%) were self-employed, 32 (7.48%) were unemployed at the time of participation, and 23 (5.37%) were retired or reported another employment status. Participants were recruited from several Canadian provinces, with 183 women (42.76%) residing in Ontario, 82 (19.16%) in British Columbia, 76 (17.76%) in Alberta, 57 (13.32%) in Quebec,

and 30 (7.01%) in other provinces or territories. The demographic distribution therefore reflected substantial variation in age, education, employment status, marital status, and geographic location, providing a heterogeneous

sample for examining the predictive contribution of emotional, cognitive, and social features to psychological well-being.

Table 1

Descriptive Statistics and Correlations Among the Study Variables

Variable	M	SD	1	2	3	4	5	6	7	8	9
1. Psychological well-being	71.64	10.83	—								
2. Cognitive reappraisal	28.91	6.14	.49***	—							
3. Expressive suppression	15.72	4.89	-.31***	-.18***	—						
4. Emotional intelligence	84.37	12.46	.58***	.42***	-.27***	—					
5. Cognitive flexibility	53.28	9.71	.61***	.39***	-.30***	.51***	—				
6. Self-efficacy	31.74	5.62	.64***	.41***	-.29***	.54***	.59***	—			
7. Mindfulness	61.39	10.16	.55***	.36***	-.38***	.47***	.52***	.50***	—		
8. Perceived social support	59.86	11.58	.60***	.34***	-.25***	.46***	.48***	.49***	.43***	—	
9. Social connectedness	46.52	8.94	.57***	.31***	-.33***	.44***	.45***	.47***	.46***	.62***	—
10. Loneliness	39.27	10.41	-.63***	-.35***	.40***	-.49***	-.50***	-.52***	-.51***	-.58***	-.67***

As shown in Table 1, all emotional, cognitive, and social variables demonstrated statistically significant associations with psychological well-being in the theoretically expected directions. Psychological well-being was positively and most strongly associated with self-efficacy ($r = .64$, $p < .001$), cognitive flexibility ($r = .61$, $p < .001$), perceived social support ($r = .60$, $p < .001$), emotional intelligence ($r = .58$, $p < .001$), social connectedness ($r = .57$, $p < .001$), mindfulness ($r = .55$, $p < .001$), and cognitive reappraisal ($r = .49$, $p < .001$). In contrast, psychological well-being was negatively associated with loneliness ($r = -.63$, $p < .001$) and expressive suppression ($r = -.31$, $p < .001$). These findings indicated that women reporting greater perceived competence, more flexible cognitive functioning, stronger social resources, greater emotional intelligence, higher present-moment awareness, and more frequent use of cognitive reappraisal also tended to report higher psychological well-being. Conversely, greater loneliness

and more frequent suppression of emotional expression were associated with lower levels of well-being. The correlations among predictor variables were generally moderate rather than excessively high. The strongest relationship among the predictors was the negative correlation between social connectedness and loneliness ($r = -.67$, $p < .001$), followed by the association between perceived social support and social connectedness ($r = .62$, $p < .001$). These relationships were conceptually consistent because women who experienced a greater sense of belonging and interpersonal integration also tended to report lower social isolation and stronger perceptions of available social support. Importantly, none of the correlations among the predictors approached a level indicating near redundancy, suggesting that the emotional, cognitive, and social features provided overlapping but distinguishable information that could contribute meaningfully to the artificial neural network model.

Table 2

Artificial Neural Network Architecture and Data Partitioning

Model Characteristic	Specification
Total sample	428
Training sample	300 (70.09%)
Validation sample	64 (14.95%)
Testing sample	64 (14.95%)
Number of input features	9
Input variables	Cognitive reappraisal, expressive suppression, emotional intelligence, cognitive flexibility, self-efficacy, mindfulness, perceived social support, social connectedness, loneliness
Hidden layers	2
Neurons in first hidden layer	12
Neurons in second hidden layer	6

Hidden-layer activation function	Rectified Linear Unit
Output neurons	1
Output activation	Linear
Optimization algorithm	Adam
Loss function	Mean squared error
Initial learning rate	0.001
Maximum training epochs	500
Early-stopping patience	30 epochs
Epoch of best validation performance	137
Final epoch	167

Table 2 presents the final structure of the multilayer perceptron artificial neural network selected for prediction of psychological well-being. The 428 participants were randomly divided into a training sample of 300 women, a validation sample of 64 women, and an independent testing sample of 64 women. The training sample represented 70.09% of the complete dataset, whereas the validation and testing samples each represented 14.95%. Nine standardized psychological predictors were included in the input layer, covering emotional features, including cognitive reappraisal, expressive suppression, and emotional intelligence; cognitive features, including cognitive flexibility, self-efficacy, and mindfulness; and social features, including perceived social support, social connectedness, and loneliness. Several candidate network architectures were examined during model development. The final network included two hidden layers containing 12 and 6 neurons,

respectively. Rectified Linear Unit activation functions were applied in the hidden layers, while a linear activation function was used in the single output neuron because psychological well-being was modeled as a continuous outcome. The network was trained using the Adam optimization algorithm and mean squared error as the loss function, with an initial learning rate of .001. Although a maximum of 500 epochs was permitted, early stopping was used to minimize overfitting. The lowest validation error was obtained at epoch 137, and training was terminated after 167 epochs when validation performance had failed to improve for 30 consecutive epochs. The divergence between the maximum permitted number of epochs and the actual stopping point indicated that the early-stopping procedure effectively prevented unnecessary continuation of training after the model had reached its best generalization performance.

Table 3

Predictive Performance of the Artificial Neural Network Across Training, Validation, and Testing Samples

Dataset	MSE	RMSE	MAE	R ²	Correlation Between Observed and Predicted Scores
Training	25.81	5.08	4.02	.78	.89
Validation	31.92	5.65	4.47	.73	.86
Testing	33.41	5.78	4.61	.71	.85
Overall sample	27.88	5.28	4.18	.76	.88

As indicated in Table 3, the artificial neural network demonstrated substantial predictive accuracy across all three subsets of the data. In the training sample, the model produced a mean squared error of 25.81, a root mean squared error of 5.08, and a mean absolute error of 4.02. The training-set coefficient of determination was $R^2 = .78$, indicating that approximately 78% of the variability in psychological well-being scores was accounted for by the emotional, cognitive, and social input features within the training data. The correlation between observed and predicted scores in the training set was .89, demonstrating a strong correspondence

between the actual psychological well-being scores and the scores estimated by the neural network. Performance remained strong in the validation sample, where RMSE increased only moderately to 5.65 and MAE to 4.47, while R^2 remained .73. The correlation between observed and predicted scores was .86 in the validation sample. Most importantly, the independent testing sample, which was not used for model fitting or hyperparameter selection, yielded an RMSE of 5.78, an MAE of 4.61, and an R^2 of .71. Thus, approximately 71% of the variance in psychological well-being among previously unseen participants was explained

by the final model. The correlation of .85 between observed and predicted values in the test sample further indicated strong out-of-sample predictive correspondence. Across the full sample, the model achieved an RMSE of 5.28, an MAE of 4.18, and an R^2 of .76. Given that the standard deviation of psychological well-being in the full sample was 10.83, an overall RMSE of 5.28 represented an average prediction error of less than one-half of a standard deviation of the outcome measure. Furthermore, the relatively small

differences between training, validation, and test performance suggested that the model did not exhibit substantial overfitting. If overfitting had occurred, substantially better training performance accompanied by pronounced deterioration in validation and test performance would have been expected. Instead, the testing R^2 remained only .07 below the training R^2 , supporting the generalizability and stability of the final predictive model.

Figure 1

Observed Versus Artificial Neural Network-Predicted Psychological Well-Being Scores in the Independent Testing Sample

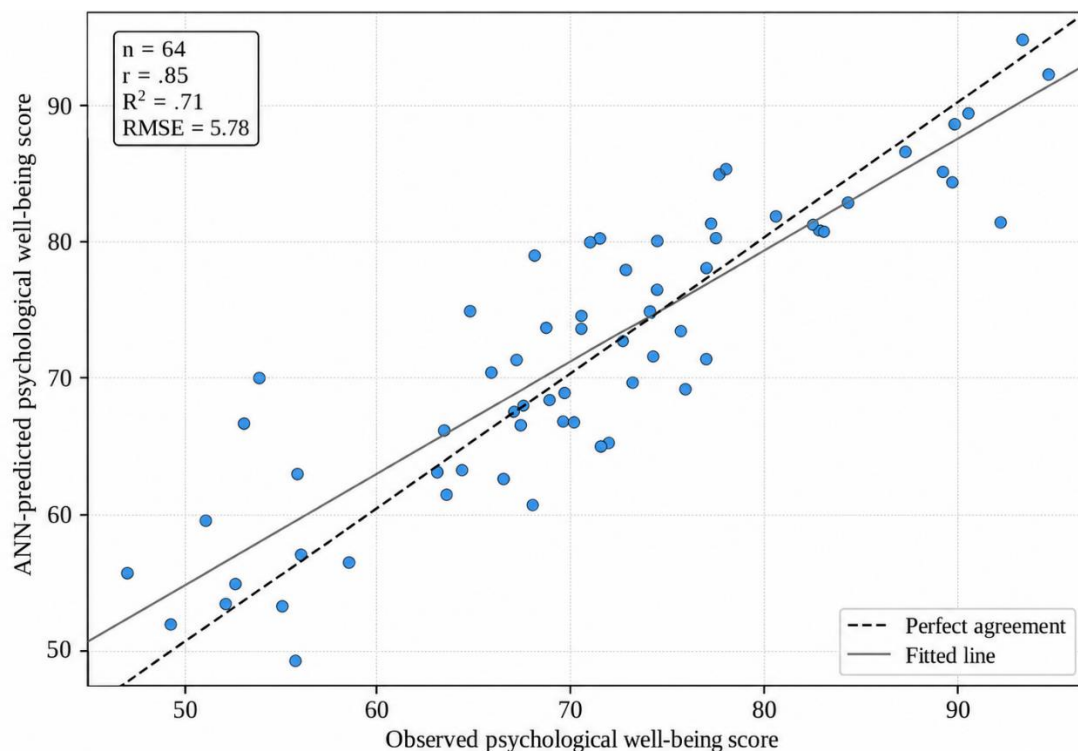


Figure 1 illustrates the correspondence between observed psychological well-being scores and the scores generated by the artificial neural network in the independent testing sample. The distribution of predicted values closely followed the observed values across most of the psychological well-being continuum, with predictions clustering around the line representing perfect agreement between observed and predicted scores. The pattern was consistent with the strong correlation reported for the test sample ($r = .85$) and with the test-set coefficient of determination of .71. Prediction errors were generally dispersed without a pronounced systematic pattern, indicating that the model did not consistently overestimate

or underestimate psychological well-being across the central range of scores. Some degree of regression toward the mean was apparent at the most extreme observed values, with very low psychological well-being scores tending to be predicted slightly higher and very high scores tending to be predicted slightly lower. Such a pattern is common in predictive regression models because extreme observations are less frequent in the training sample and therefore provide less information for optimization. Nevertheless, the overall proximity of predicted values to the observed values indicated that the network successfully learned a substantial proportion of the nonlinear and interactive information contained in the emotional, cognitive, and social predictors.

Table 4*Normalized Importance of Emotional, Cognitive, and Social Features in Predicting Psychological Well-Being*

Predictor	Feature Domain	Importance	Normalized Importance (%)	Rank
Self-efficacy	Cognitive	.184	100.00	1
Loneliness	Social	.171	92.93	2
Cognitive flexibility	Cognitive	.153	83.15	3
Perceived social support	Social	.139	75.54	4
Emotional intelligence	Emotional	.121	65.76	5
Social connectedness	Social	.096	52.17	6
Mindfulness	Cognitive	.065	35.33	7
Cognitive reappraisal	Emotional	.045	24.46	8
Expressive suppression	Emotional	.026	14.13	9

As presented in Table 4, self-efficacy emerged as the most influential input variable in the artificial neural network, with a raw importance value of .184 and a normalized importance of 100%. This result indicated that participants' perceived ability to manage challenges, solve problems, and exert effective personal agency contributed more strongly to the model's predictions of psychological well-being than any other individual feature. Loneliness was the second most important predictor, with a normalized importance of 92.93%, indicating that perceived social isolation provided substantial predictive information even after the neural network simultaneously incorporated social support, social connectedness, emotional characteristics, and cognitive resources. Cognitive flexibility ranked third, with a normalized importance of 83.15%, suggesting that the capacity to reconsider situations, generate alternative interpretations, and adapt cognitive responses to changing circumstances was another central determinant of the

model's predictions. Perceived social support was the fourth most influential predictor at 75.54%, followed by emotional intelligence at 65.76% and social connectedness at 52.17%. Mindfulness showed a more moderate contribution, with normalized importance of 35.33%, whereas cognitive reappraisal and expressive suppression showed comparatively smaller contributions of 24.46% and 14.13%, respectively. The lower relative importance of expressive suppression should not be interpreted as evidence that suppression was unrelated to psychological well-being, because the bivariate analysis demonstrated a significant negative correlation between suppression and well-being. Rather, its lower neural-network importance indicated that, after considering the full set of emotional, cognitive, and social variables simultaneously, suppression contributed less unique predictive information than stronger features such as self-efficacy, loneliness, and cognitive flexibility.

Table 5*Aggregated Predictive Contribution of Emotional, Cognitive, and Social Feature Domains*

Feature Domain	Included Predictors	Total Relative Contribution (%)	Mean Importance	Predictor Rank	Domain Rank
Cognitive	Cognitive flexibility, self-efficacy, mindfulness	40.20	.134	1	1
Social	Perceived social support, social connectedness, loneliness	40.60	.135	2	2
Emotional	Cognitive reappraisal, expressive suppression, emotional intelligence	19.20	.064	3	3

Table 5 summarizes the relative contribution of the three broader feature domains after the importance values of conceptually related predictors were aggregated. Social features accounted for 40.60% of the total model importance, while cognitive features accounted for a nearly equivalent 40.20%. Emotional features accounted for the remaining 19.20%. Although the social domain had the numerically highest aggregated contribution, its advantage

over the cognitive domain was only 0.40 percentage points, indicating that social and cognitive characteristics contributed almost equally to prediction of psychological well-being. This pattern suggests that psychological well-being among the women in this study was not dominated by a single psychological domain. Instead, accurate prediction depended particularly on the combination of internal cognitive resources and interpersonal social experiences.

Within the cognitive domain, self-efficacy and cognitive flexibility accounted for most of the predictive influence, while within the social domain, loneliness and perceived social support were the strongest contributors. The emotional domain contributed less overall, but emotional intelligence remained an individually meaningful predictor and ranked fifth among all nine input variables. Consequently, the neural network results indicated that emotional characteristics remained relevant, but their predictive value was partly shared with or complemented by more influential cognitive and social features. Taken together, the domain-level findings support a multidimensional interpretation of psychological well-being in which beliefs about personal competence, adaptive cognitive functioning, interpersonal connectedness, perceived support, and freedom from loneliness collectively provide the strongest predictive information.

Overall, the findings demonstrated that psychological well-being could be predicted with substantial accuracy from a multidimensional set of emotional, cognitive, and social features. The artificial neural network accounted for 71% of the variance in psychological well-being in the independent testing sample, indicating that the predictive relationships learned from the training data generalized effectively to observations not involved in model estimation. The relatively similar prediction errors across the training, validation, and testing samples supported the stability of the network and provided little evidence of serious overfitting. At the individual predictor level, self-efficacy, loneliness, cognitive flexibility, perceived social support, and emotional intelligence constituted the most influential features. At the broader domain level, cognitive and social predictors contributed almost equally and together accounted for more than four-fifths of total predictive importance. These results suggest that women's psychological well-being reflects a complex configuration of personal cognitive resources and interpersonal social experiences rather than a simple linear dependence on a single emotional, cognitive, or social factor. The artificial neural network was therefore able to integrate multiple correlated predictors and identify their combined predictive structure while maintaining strong performance in an independent test sample.

4. Discussion

The present study examined the prediction of psychological well-being among women in Canada using emotional, cognitive, and social features within an artificial

neural network framework. The findings demonstrated that the selected features collectively provided strong predictive information, with the final model explaining 71% of the variance in psychological well-being in the independent testing sample. The model also showed a high correlation between observed and predicted scores and relatively comparable performance across the training, validation, and testing datasets, suggesting good generalizability and limited overfitting. At the level of individual predictors, self-efficacy emerged as the most influential feature, followed by loneliness, cognitive flexibility, perceived social support, emotional intelligence, social connectedness, mindfulness, cognitive reappraisal, and expressive suppression. At the broader domain level, cognitive and social variables made nearly equivalent contributions and together accounted for the majority of predictive importance, whereas emotional features made a smaller but still meaningful contribution. These findings support a multidimensional conceptualization of psychological well-being and indicate that well-being is better understood through the simultaneous consideration of personal cognitive resources, emotional competencies, and interpersonal experiences rather than through isolated predictors.

The strong overall predictive performance of the artificial neural network is consistent with the growing body of research demonstrating the value of machine-learning approaches in mental health prediction. Previous studies have shown that nonlinear models can successfully integrate multiple psychological, behavioral, and contextual characteristics when predicting outcomes such as anxiety, depression, post-traumatic stress, and social anxiety (Hossain et al., 2025; Liu, 2024; Wang et al., 2025). The present findings extend this line of research by demonstrating that a similar approach can be applied effectively to a positive psychological outcome rather than exclusively to psychopathology. Predictive models of post-traumatic stress disorder, complex post-traumatic stress disorder, depression, and anxiety have shown that combinations of risk and protective variables may achieve greater predictive value than isolated factors (Memarzia et al., 2024). Likewise, work using machine-learning approaches to examine psychological and neurobiological features has emphasized that complex outcomes are often best represented through multivariable patterns rather than single predictors (Fabrizio et al., 2025; Grecucci et al., 2023). The present neural network results are consistent with this principle, as predictive accuracy depended on the

integrated contribution of emotional, cognitive, and social features.

Self-efficacy was identified as the most influential predictor of psychological well-being. This finding suggests that women who perceive themselves as capable of managing difficulties, solving problems, and responding effectively to environmental demands are more likely to experience higher levels of positive psychological functioning. Self-efficacy may contribute to well-being through several mechanisms. Individuals with stronger self-efficacy are more likely to approach difficult situations as manageable challenges rather than uncontrollable threats, persist in the face of setbacks, and mobilize adaptive coping resources. Such processes may strengthen autonomy, environmental mastery, goal-directed behavior, and personal growth, all of which are closely related to psychological well-being. The result is compatible with research showing that positive psychological resources can attenuate the adverse effects of perceived stress and support mental health (Liu et al., 2023). It is also consistent with broader evidence indicating that resilience and adaptive psychological functioning are associated with better psychosocial outcomes and reduced symptom burden (Fabrizio et al., 2024; Yeo et al., 2021). The high predictive importance of self-efficacy therefore indicates that perceptions of personal competence may function as a central cognitive resource connecting stress appraisal, coping, and psychological well-being.

Loneliness was the second strongest predictor and showed a substantial negative association with psychological well-being. This finding underscores the importance of perceived social isolation as a major determinant of psychological functioning. Loneliness differs from objective social isolation because it reflects the subjective perception that one's relationships are insufficient in quantity or quality. As such, an individual can experience loneliness even in the presence of frequent social contact. Prior research has demonstrated meaningful associations between social and emotional loneliness and cognitive as well as psychological functioning (Carbone et al., 2022). Similarly, social loneliness has been identified as an important correlate of clinical and psychological characteristics in vulnerable populations (Crespo et al., 2024). The present findings extend these observations to a nonclinical female sample and suggest that loneliness may exert a particularly strong influence on well-being when considered simultaneously with support, connectedness, emotional functioning, and cognitive resources. Its high

neural-network importance may indicate that loneliness captures a uniquely negative interpersonal experience that cannot be fully explained by simply measuring the availability of social support.

The importance of loneliness is also consistent with contemporary health psychology research emphasizing the influence of social relationships on both psychological and physical health (Cundiff et al., 2025). Social environments may shape emotional regulation, stress reactivity, perceived safety, and behavioral adaptation. Persistent loneliness can therefore affect several pathways simultaneously, including negative self-evaluation, reduced perceived belonging, heightened stress sensitivity, and diminished motivation to engage with the social environment. In digital contexts, these processes may be intensified through social comparison and online interaction. Social comparison has been associated with well-being outcomes (Elbayomy & Metwally, 2023), and problematic use of social networks has been linked to stress through mechanisms such as fear of missing out (Fu et al., 2023). The present study did not directly measure digital behavior, but the strong influence of loneliness suggests that perceived interpersonal disconnection remains highly relevant even in environments characterized by constant technological connectivity.

Cognitive flexibility emerged as the third most important predictor, reinforcing the role of adaptive cognitive processing in psychological well-being. Cognitive flexibility enables individuals to revise interpretations, consider alternative responses, and adjust to changing demands. Women with greater cognitive flexibility may therefore be better able to reframe stressful experiences, modify ineffective strategies, and preserve a sense of control in uncertain circumstances. This interpretation aligns with research emphasizing the interaction between cognitive and emotional processes in psychological functioning. Studies of emotion regulation have demonstrated that adaptive cognitive processes can mediate the relationship between stress and psychological symptoms (Liu et al., 2023). Similarly, maladaptive beliefs have been associated with both symptomatology and difficulties in cognitive reappraisal (Tecuta et al., 2021). The high importance of cognitive flexibility in the present model therefore supports the proposition that the ability to alter cognitive responses is a key mechanism through which individuals maintain positive functioning under changing conditions.

Perceived social support was another major predictor of psychological well-being and ranked fourth in the neural network. This result indicates that the perception that

assistance, understanding, and emotional resources are available from family, friends, and significant others is strongly related to positive psychological functioning. Social support may buffer the psychological impact of stress by providing practical assistance, emotional validation, and opportunities for adaptive coping. It may also contribute directly to feelings of belonging, self-worth, and interpersonal security. The finding complements the strong role of loneliness and demonstrates that social functioning includes both positive and negative dimensions. Social support and loneliness were strongly related but not interchangeable, suggesting that each captured distinct aspects of interpersonal experience. This interpretation is compatible with evidence that social relationships influence health through multiple pathways, including emotional, behavioral, and physiological mechanisms (Cundiff et al., 2025). It also reinforces findings that social and emotional loneliness are independently associated with psychological functioning (Carbone et al., 2022).

Emotional intelligence also demonstrated meaningful predictive importance, ranking fifth among the nine predictors. This finding suggests that the ability to perceive, interpret, and manage emotional information contributes to psychological well-being even when cognitive and social resources are simultaneously considered. Emotional intelligence may facilitate better recognition of emotional states, more appropriate regulation strategies, improved interpersonal communication, and more adaptive responses to conflict or stress. Research examining interpersonal emotion regulation has shown that social-affective demands interact with cognitive functioning and working memory, particularly in emotionally challenging contexts (Krause-Utz et al., 2025). This supports the view that emotional competence is not independent of cognition but operates through coordinated affective and cognitive mechanisms. The present results further suggest that emotional intelligence may be more broadly predictive of well-being than specific regulation strategies considered in isolation.

Social connectedness ranked sixth and made a moderate contribution to prediction. This finding reflects the importance of a broader sense of belonging and interpersonal integration. Whereas perceived social support concerns the availability of help and loneliness reflects perceived relational deficiency, social connectedness represents the extent to which an individual feels embedded in meaningful social relationships. Its contribution to the network suggests that psychological well-being is partly rooted in the subjective experience of being connected to others. This

interpretation is consistent with theoretical models emphasizing that interpersonal processes are central to mental health and may influence emotional regulation and self-understanding (Chatterjee & Rai, 2023). Moreover, the increasing role of digital communication may alter the ways social connectedness is formed or disrupted. Personality and technology-related behavior have been linked to interpersonal difficulties and problematic digital engagement (Mejia-Suazo et al., 2025), while online behavioral data have been shown to contain psychologically meaningful information related to mood and personality (Ao & Xia, 2026). Together, these studies support the view that social connectedness is a multidimensional construct with relevance across both offline and digital environments.

Mindfulness made a smaller but still meaningful contribution to the neural network. This may indicate that present-moment awareness and attentional regulation support psychological well-being but overlap with broader cognitive and emotional processes. Mindfulness may facilitate awareness of distress without immediate reactive behavior, allowing individuals to respond more adaptively to internal experiences. Its moderate relative importance should therefore not be interpreted as evidence of low relevance. Rather, neural-network importance reflects unique predictive contribution after all other variables have been considered. Contemporary mental health research increasingly recognizes that interventions targeting attention, experiential engagement, and cognitive-emotional processing can affect anxiety and depressive symptoms through multiple mechanisms (Chen et al., 2026). The present findings suggest that mindfulness may be one component of this broader regulatory system.

Cognitive reappraisal was positively associated with psychological well-being but showed relatively lower predictive importance than self-efficacy, cognitive flexibility, and emotional intelligence. This result may reflect conceptual overlap between cognitive reappraisal and other adaptive cognitive variables. Reappraisal involves changing the interpretation of a situation in order to modify its emotional impact, and this process likely depends partly on cognitive flexibility and perceived competence. Thus, when these related variables were entered simultaneously into the artificial neural network, some of the predictive variance associated with reappraisal may have been captured by broader cognitive resources. This explanation is consistent with previous research linking cognitive reappraisal with adaptive emotional functioning and demonstrating its interaction with irrational beliefs and

symptom patterns (Tecuta et al., 2021). The present findings therefore do not diminish the theoretical importance of reappraisal but instead indicate that its contribution to well-being may be embedded within a wider cognitive-regulatory system.

Expressive suppression had the lowest relative importance and was negatively associated with psychological well-being. This pattern is theoretically coherent because suppression may reduce visible emotional expression without changing the underlying emotional experience. Persistent reliance on suppression may therefore increase emotional effort, interfere with interpersonal communication, and reduce opportunities for social support. However, its comparatively low neural-network importance suggests that its unique contribution was limited after more influential cognitive and social variables were taken into account. This finding also reinforces the distinction between statistical association and predictive importance. A variable can be significantly correlated with an outcome while contributing relatively little additional information to a multivariable predictive model. Such distinctions demonstrate the value of machine-learning methods in psychological research.

The domain-level analysis showed that cognitive and social features contributed almost equally to prediction and together accounted for the vast majority of total feature importance. This is one of the most important findings of the study. It suggests that psychological well-being among women is determined neither primarily by intrapersonal cognition nor primarily by interpersonal relationships, but rather by their combination. Strong personal agency and adaptive thinking may be insufficient when social isolation is severe, while supportive relationships may not fully compensate for low self-efficacy or rigid cognitive functioning. This interpretation is consistent with research emphasizing that psychological resilience, symptom development, and functioning arise from the interaction of multiple systems (Fabrizio et al., 2025). It also aligns with work showing that psychological outcomes may be influenced simultaneously by external conditions and internal vulnerability or protective factors (Shi et al., 2026). The near-equal contribution of cognitive and social domains therefore supports an integrative model of well-being.

The relatively smaller contribution of the emotional domain should also be interpreted cautiously. Emotional variables remained significantly associated with psychological well-being, and emotional intelligence was among the more important individual predictors. The lower

aggregated contribution may simply indicate that emotional functioning is partly expressed through cognitive and social pathways. Emotion regulation can influence cognition, and social relationships often provide contexts in which emotional processes occur. Research on psychopathology repeatedly demonstrates this interdependence. For example, trauma-related outcomes involve complex interactions among emotional, cognitive, physiological, and contextual processes (Burback et al., 2024; Jowf et al., 2023), while the trajectories of depressive disorders vary substantially across individuals and may reflect multiple underlying mechanisms (Atagün, 2025). Therefore, the present findings should not be interpreted as suggesting that emotional functioning is unimportant, but rather that its predictive effects operate within a broader psychological system.

The strong model performance also has methodological implications. The similarity of predictive accuracy across training, validation, and testing subsets suggests that the final neural network captured generalizable relationships rather than merely memorizing the training data. This is especially important in psychological prediction, where complex models can easily overfit limited samples. The findings support the usefulness of multilayer perceptron networks for modeling multidimensional psychological data and are consistent with prior research showing successful application of machine learning to mental health prediction (Liu, 2024; Wang et al., 2025). At the same time, predictive performance should be understood in the context of measurement quality, sample composition, and validation design. Research using digital biomarkers and other computational approaches similarly emphasizes the importance of robust validation before predictive models are translated into clinical or practical applications (Garzón-Partida et al., 2025). Advances in ecological momentary assessment and real-time monitoring also suggest that future prediction may become increasingly dynamic rather than relying solely on cross-sectional questionnaires (Rapelli et al., 2025).

5. Conclusion

The present findings contribute to the broader movement toward precision approaches in mental health research. Precision-oriented models seek to identify patterns that can distinguish individuals rather than relying only on average group-level associations. This approach is especially relevant because psychological outcomes often demonstrate considerable heterogeneity. Research on depressive

trajectories has highlighted meaningful variation in clinical courses (Atagün, 2025), while predictive work in trauma and neurological conditions has shown that multiple pathways may lead to similar symptom profiles (Mavroudis et al., 2025; Memarzia et al., 2024). The present findings suggest that psychological well-being may likewise be understood more accurately through individualized configurations of cognitive, emotional, and social resources. In this sense, the ANN model provides not only a statistical prediction but also a framework for identifying which domains may be most relevant to an individual's well-being profile.

6. Limitations and Suggestions

Several limitations should be considered when interpreting the present findings. First, the cross-sectional design prevents causal conclusions regarding the relationships among emotional, cognitive, social features, and psychological well-being. Although the artificial neural network demonstrated strong predictive performance, prediction does not establish temporal or causal direction. Second, participants were recruited using convenience and voluntary response sampling, which may have introduced selection bias and may limit the generalizability of the findings to all women living in Canada. Women with greater interest in psychological well-being or greater familiarity with online surveys may have been more likely to participate. Third, the study relied primarily on self-report questionnaires, creating the possibility of common-method variance, social desirability effects, and response bias. Fourth, although the sample size was adequate for the selected ANN architecture, larger datasets would permit more complex modeling, stronger external validation, and potentially more stable estimation of feature importance. Fifth, the model was validated using an internal holdout test sample rather than an entirely independent external sample, and predictive performance may therefore differ when applied to women from different regions, cultural backgrounds, or socioeconomic contexts. Finally, the study focused on a selected group of emotional, cognitive, and social predictors and did not include other potentially important determinants of psychological well-being such as physical health, income, caregiving burden, occupational stress, discrimination, sleep, physical activity, major life events, or biological indicators.

Future studies should use longitudinal designs to examine whether emotional, cognitive, and social features predict subsequent changes in psychological well-being and to

determine the temporal ordering of these relationships. Replication in larger and more diverse samples is needed, including women from different cultural, socioeconomic, linguistic, and regional backgrounds. External validation using an independent dataset would provide a stronger test of model generalizability. Researchers should also compare artificial neural networks with alternative machine-learning methods such as random forests, gradient boosting, support vector regression, and elastic-net regression to determine whether the observed performance is architecture-specific. Future studies may benefit from incorporating behavioral, physiological, and digital indicators alongside self-report measures, including sleep, physical activity, smartphone use, ecological momentary assessment, and wearable-sensor data. Explainable artificial intelligence techniques should also be used to clarify nonlinear relationships, thresholds, and interactions among predictors. Particular attention should be given to whether combinations of self-efficacy, loneliness, cognitive flexibility, and social support identify distinct psychological well-being profiles. Finally, intervention studies could examine whether deliberate changes in the most influential predictors result in corresponding improvements in well-being and whether predictive models can be used to identify individuals most likely to benefit from particular interventions.

The findings have several practical implications for psychological and community-based programs designed to promote women's well-being. Assessment strategies should move beyond a narrow focus on emotional distress and include evaluation of self-efficacy, cognitive flexibility, loneliness, social support, and connectedness. Because self-efficacy was the strongest predictor, interventions may benefit from emphasizing mastery experiences, problem-solving, goal setting, graded task achievement, and reinforcement of personal competence. Cognitive-flexibility training may also be useful for helping women reconsider rigid interpretations, generate alternative solutions, and adapt more effectively to changing demands. The strong contribution of loneliness and perceived social support suggests that individual psychological interventions should be complemented by social and community strategies that strengthen meaningful relationships, peer support, and social participation. Screening systems could incorporate brief multidimensional measures to identify women with combinations of low self-efficacy, high loneliness, low cognitive flexibility, and weak perceived support. In settings where digital mental-health tools are used, predictive models may eventually assist professionals in tailoring preventive

interventions, provided that such systems are transparent, ethically governed, and used to support rather than replace professional judgment. Overall, the results indicate that efforts to promote psychological well-being should integrate cognitive empowerment with social connection and emotional skill development rather than treating these domains separately.

Authors' Contributions

Authors contributed equally to this article.

Declaration

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

Transparency Statement

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

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

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

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