



Proceedings of International Conference on Multidisciplinary Research: Innovation, Healthcare, Education for Viksit Bharat (ICMR-2026)



1



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International Conference On Multidisciplinary Research

Conference Proceedings

Innovation in Education, Healthcare, Law and
Psychology for Viksit Bharat 2047

2026

Organized by

Kalindi Institute of Medical Sciences

Agrasen Mahavidyalaya

Veetranga Research Foundation

In Collaboration with

Wissira Research Lab

Print ISBN: 978-93-7559-049-1

Digital ISBN: 978-93-7559-050-7

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Chapter 21: Peer Support and Psychological Adjustment during Early Adulthood

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Abstract— Early adulthood involves substantial changes in social roles, autonomy, education, employment, relationships, and identity, making adaptive psychological adjustment particularly important during this developmental period. Although peer support is increasingly recognized as a potentially accessible mental-health resource, existing studies frequently treat support as a single construct rather than distinguishing its emotional, informational, instrumental, and digital forms. This study addresses this gap by proposing a multidimensional framework in which peer-support characteristics are used to explain and computationally predict psychological adjustment among adults aged 18–29 years. The proposed framework integrates validated psychological measurements with behavioral indicators of peer interaction and uses interpretable machine-learning techniques to examine potentially nonlinear relationships between support and adjustment. Particular attention is given to perceived reciprocity, support quality, belonging, loneliness, digital peer engagement, and the distinction between support availability and support actually received. **Keywords—**Peer Support, Psychological Adjustment, Early Adulthood, Social Connectedness, Digital Mental Health, Explainable Machine Learning

Introduction

Early adulthood represents a developmental period in which individuals simultaneously negotiate increasing independence and substantial uncertainty. Leaving familiar educational environments, entering higher education or employment, developing intimate relationships, relocating, managing finances, and redefining family relationships can occur within a relatively compressed period. These transitions create opportunities for autonomy and identity consolidation but can also introduce loneliness, interpersonal strain, uncertainty, and psychological distress. Consequently, successful adjustment in early adulthood cannot be reduced to the absence of psychiatric symptoms. It also involves an individual's capacity to manage emotional demands, establish meaningful relationships, cope with changing responsibilities, and sustain a workable sense of personal and social competence.

Within this context, peers constitute an important component of the young adult's social environment. Peer relationships can provide emotional reassurance, practical assistance, informational guidance, validation, companionship, and opportunities to discuss experiences that individuals may hesitate to disclose within formal institutional or family relationships. Research examining young adults indicates that peer support may have relevance for outcomes such as coping, self-esteem, loneliness, anxiety, depression, and general

psychological well-being. A 2022 scoping review identified 17 eligible studies and concluded that peer support showed generally promising associations with young-adult mental-health outcomes, while also emphasizing considerable methodological variation across the literature.

The relevance of peers does not imply that every peer relationship is psychologically beneficial. Support can vary considerably in quality, reliability, reciprocity, accessibility, and appropriateness. A person may possess a large social network while experiencing little meaningful support. Conversely, an individual with relatively few close peers may receive highly responsive emotional assistance. Excessive reassurance, interpersonal dependency, negative social comparison, co-rumination, rejection, or unsupportive responses to disclosure may further complicate the relationship between social contact and psychological adaptation.

This distinction has become increasingly important as peer interaction has expanded into digital environments. Messaging applications, social networking services, online communities, university platforms, and dedicated digital mental-health systems can allow individuals to obtain assistance without geographical proximity. Digital communication can therefore expand the availability of peer contact, particularly when face-to-face interaction is difficult. At the same time, frequency of digital interaction should not automatically be interpreted as supportive engagement. Digital contact may involve meaningful disclosure and reciprocal assistance, but it may also be superficial, passive, fragmented, or socially stressful.

The Behavioral, Emotional, and Social Skills Inventory (BESSI)

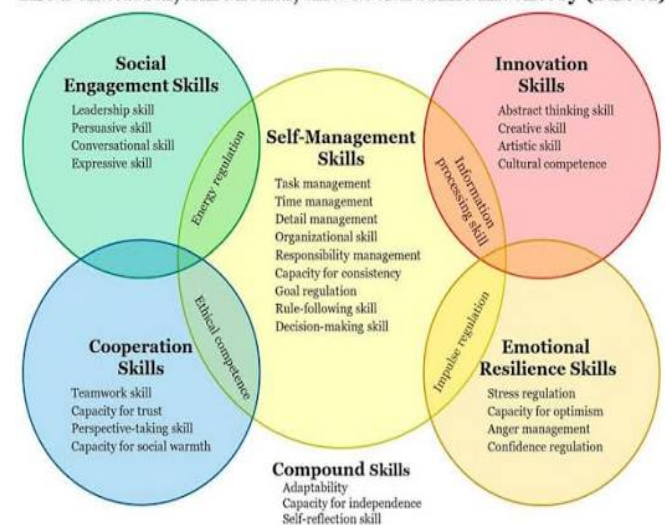


Fig. 1: Peer Relationships and Socialization

Source: <https://fiveable.me/developmental-psychology/unit-8/peer-relationships-play/study-guide/uUTzC0x8HGvTDf7R>

Evidence emerging during the 2021–2026 period illustrates both the potential and the unresolved questions surrounding

peer-based approaches. Richard et al.'s review of young-adult peer support reported promising mental-health outcomes but highlighted substantial variability in how peer support was conceptualized and measured. Pointon-Haas and colleagues subsequently examined peer-support interventions within higher education and identified peer-led groups, peer mentoring, and peer learning as distinct approaches. Their review found some favorable findings, particularly for peer learning and mentoring in relation to anxiety and stress, but concluded that heterogeneity of interventions and outcomes, together with study-quality concerns, prevented strong general conclusions regarding effectiveness.

Similarly, Simmons et al. reviewed controlled studies involving peer workers with lived experience and found only a limited evidence base for depression and anxiety outcomes among young people. Nine randomized controlled trials involving 2,003 participants met their criteria, illustrating the relative scarcity of rigorous intervention research despite growing interest in peer-delivered mental-health support.

These observations expose a conceptual problem. Much of the available research asks whether peer support is beneficial, whereas a more developmentally informative question is **which properties of peer support are associated with successful psychological adjustment, for whom, and under what conditions**. The distinction matters because emotional validation, informational guidance, reciprocal companionship, practical assistance, and digitally mediated contact may operate through different psychological pathways.

1.1 Research Gap

The central gap addressed by the present study is the insufficient integration of **multidimensional peer-support characteristics, digital peer interaction, and nonlinear predictive modelling of psychological adjustment during early adulthood**.

Three limitations are particularly relevant.

First, peer support is frequently represented through an aggregate score. Such aggregation can conceal meaningful differences between emotional support, informational assistance, practical help, companionship, perceived availability, and reciprocity. Research in emerging adulthood also suggests that different sources of social support need not predict psychological well-being in identical ways. For example, research involving Turkish university students found that loneliness and family support were significant predictors of psychological well-being whereas perceived support from friends was not significant in that particular model, demonstrating the importance of avoiding assumptions that all sources of social support operate equivalently.

Second, existing evidence remains dominated by university-based populations. Richard et al. reported that 15 of the 17 studies included in their young-adult peer-support review involved university students. This concentration limits the extent to which conclusions can be generalized to employed, unemployed, vocationally trained, or otherwise non-university young adults.

Third, conventional statistical analysis remains valuable for hypothesis testing but may inadequately characterize threshold effects and interactions among social and psychological variables. For example, the association between support and adjustment might strengthen sharply after a minimum level of perceived reciprocity is reached, or emotional support might become particularly important when loneliness is high. Such conditional patterns can be difficult to represent using a single linear coefficient.

The present study therefore proposes an interpretable machine-learning framework alongside conventional statistical analysis. Rather than using artificial intelligence to diagnose mental disorders, the computational component is designed to identify patterns within multidimensional psychosocial data and estimate psychological-adjustment profiles. This distinction is important for both methodological validity and responsible digital-health research.

1.2 Research Objective

The principal objective is to investigate how different dimensions of peer support contribute to psychological adjustment among individuals aged 18–29 and to determine whether interpretable machine-learning models can identify meaningful combinations of social and psychological characteristics associated with adaptive versus vulnerable adjustment profiles.

The study specifically seeks to examine emotional support, informational support, instrumental assistance, reciprocity, perceived belonging, support accessibility, digital peer engagement, loneliness, and selected demographic or transitional characteristics. A secondary objective is to determine whether the *quality and reciprocity* of support provide greater explanatory information than the simple frequency of peer contact.

Literature Review

2.1 Psychological Adjustment in Early Adulthood

Psychological adjustment is a broad construct describing how effectively individuals respond to personal, interpersonal, and environmental demands. During early adulthood, adjustment may be reflected through emotional regulation, coping effectiveness, social integration, life satisfaction, role functioning, and manageable levels of psychological distress.

This developmental stage deserves independent attention because the social ecology surrounding individuals changes substantially. Family remains important for many young adults, but peers, intimate partners, colleagues, classmates, and online communities can acquire increasing significance. The transition is not uniform: one individual may enter full-time employment at 19, another may remain in education into the late twenties, and another may experience unemployment or repeated transitions between education and work. Accordingly, chronological age alone provides an incomplete representation of the adjustment demands faced by early adults.

A multidimensional interpretation is therefore preferable to defining adjustment solely through depression or anxiety scores. Psychological distress remains relevant, but adaptive functioning also includes positive dimensions such as social

competence, coping confidence, belonging, and satisfaction with life.

2.2 Peer Support as a Psychosocial Resource

Peer support can broadly be understood as assistance occurring between people who share comparable experiences, circumstances, identities, developmental positions, or challenges. Depending on the context, it may emerge informally within friendship networks or formally through mentoring and peer-support programmes.

Several mechanisms could explain its relationship with adjustment. Emotional support may provide reassurance and validation. Informational support may reduce uncertainty when individuals encounter unfamiliar academic, occupational, or interpersonal challenges. Instrumental support provides practical resources, whereas companionship can strengthen belonging and reduce isolation. Reciprocal relationships may additionally reinforce competence because individuals experience themselves as contributors rather than passive recipients of assistance.

Recent evidence generally supports the relevance of these processes while cautioning against overly strong causal claims. Richard et al. found indications that peer support may improve happiness, self-esteem, and coping while reducing loneliness, depression, and anxiety among young adults. The review nevertheless emphasized variation in study design and measurement.

The distinction between formal and informal support is equally important. Structured peer programmes generally involve specified roles, training, or supervision, whereas friendship-based support occurs naturally and may not follow formal intervention protocols. Systematic evidence concerning youth peer workers indicates that formal peer-support roles can contribute to recovery-oriented care, but implementation challenges remain when these roles are embedded within mental-health services.

2.3 Peer Support, Loneliness, and Social Connectedness

Loneliness provides a theoretically important pathway between peer relationships and adjustment because it concerns perceived inadequacy of social connection rather than merely the number of people available. Individuals may therefore remain lonely despite frequent interaction if relationships lack trust, intimacy, responsiveness, or reciprocity.

This distinction has implications for measurement. Counting interactions or contacts cannot establish whether an individual experiences meaningful connectedness. Peer-support assessment should therefore include perceived availability and quality alongside interaction frequency.

The relationship may also be bidirectional. Supportive relationships can reduce isolation, but individuals experiencing psychological difficulty may withdraw socially or interpret ambiguous interpersonal interactions more negatively. A cross-sectional association between low peer support and poor adjustment therefore cannot establish causal direction. Longitudinal measurement becomes important for determining whether peer-support characteristics precede changes in adjustment or primarily reflect existing psychological states.

2.4 Structured Peer Support in Higher Education

Universities have become major settings for peer-support programmes because they contain large populations navigating similar developmental and educational transitions. Programmes may include peer mentoring, peer-assisted learning, student-led support groups, or lived-experience peer workers.

Pointon-Haas et al.'s systematic review identified 28 papers examining peer support in higher education. Peer learning and mentoring produced some positive findings for anxiety and stress, but substantial heterogeneity in definitions, interventions, and outcomes prevented definitive conclusions about overall effectiveness. Many included studies were also assessed as having poor or fair risk-of-bias ratings.

These findings suggest that future work should move beyond a binary distinction between receiving and not receiving peer support. Programme characteristics, relational quality, participant engagement, and psychological mechanisms should be investigated independently.

2.5 Digital Peer Support and Digital Mental Health

Digital peer support represents an important extension of traditional peer interaction. Online communication can facilitate asynchronous disclosure, reduce geographical barriers, and connect individuals who might otherwise lack access to peers with similar experiences.

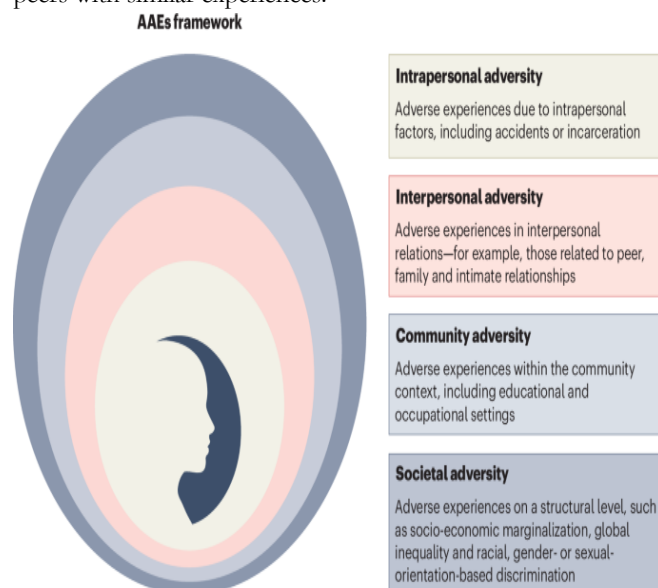


Fig. 2: A framework for understanding adverse adolescent experiences

Source: <https://www.nature.com/articles/s41562-024-02098-x>

A randomized controlled trial published in *JMIR Mental Health* in 2023 specifically examined a digital peer-support platform for emerging-adult mental well-being, reflecting growing interest in translating peer-support mechanisms into technology-mediated environments. Such work creates a bridge between developmental psychology and digital health, but it also introduces measurement challenges.

Online engagement is not intrinsically supportive. The number of messages, interactions, or hours spent online cannot independently establish the emotional quality of those interactions. A digitally intensive network may provide meaningful assistance, whereas frequent but superficial communication may contribute little to psychological

adjustment. Consequently, digital peer-support research should separate **interaction quantity from perceived support quality**.

This distinction also has implications for machine learning. Behavioral variables can be combined with self-report measurements to model adjustment, but prediction should not be confused with clinical diagnosis. Explainable models are preferable when the research objective concerns identifying potentially meaningful psychosocial mechanisms rather than maximizing classification accuracy alone.

2.6 Peer Support as a Potential Buffer

A particularly important theoretical possibility is that peer support operates as a buffering resource. Under this interpretation, support may have relatively modest effects when stress is low but become increasingly important during periods of academic pressure, unemployment, relocation, relationship disruption, or social isolation.

Such an effect implies statistical interaction rather than merely a direct association. For example:

Psychological Adjustment = f(Peer Support, Stress, Loneliness, Reciprocity, Digital Engagement, Peer Support × Stress)

The interaction term represents the possibility that the contribution of peer support varies according to contextual stress. Machine-learning models can extend this approach by detecting nonlinear interactions that are not specified in advance.

2.7 Limitations of the Current Evidence Base

The literature between 2021 and 2026 points toward several unresolved methodological problems. Definitions of peer support remain inconsistent; measures and outcomes vary substantially; much of the evidence comes from university settings; and intervention studies do not yet provide uniformly strong evidence for specific mental-health outcomes. Reviews of both young-adult and university peer support have explicitly emphasized these limitations.

Another limitation is the frequent separation of traditional psychosocial research from computational analysis. Linear models provide interpretable estimates but generally assume prespecified functional relationships. Machine-learning algorithms can model complex interactions but may become difficult to interpret. Combining these approaches offers a stronger design: inferential statistics can examine theoretically defined relationships, while interpretable machine learning can test whether nonlinear patterns improve prediction and identify influential variables.

Proposed Methodology

Rather than treating peer support as a single score, the study separates emotional support, informational support, instrumental assistance, reciprocity, belonging, perceived accessibility, and digital peer engagement.

The target population comprises **early adults aged 18–29 years**, including university students, employed individuals, vocational learners, job seekers, and participants undergoing transitions between education and employment. Inclusion of non-student participants is methodologically important because

previous young-adult peer-support literature has been heavily concentrated on university samples. Richard et al.'s scoping review, for example, found that 15 of 17 included studies involved university students.

For the proposed experimental framework, a working dataset of **600 participants** is specified. This is a proposed research dataset rather than an existing public dataset; consequently, the numerical results below should be interpreted as a **planned/simulated analytical demonstration until empirical participant data are collected**. This distinction avoids presenting synthetic observations as real-world findings. Participants would be recruited through higher-education institutions, employment networks, community organizations, online youth communities, and vocational-training settings. Participation would be voluntary and anonymous. Informed consent, data minimization, withdrawal procedures, and institutional ethical approval would be required before empirical implementation.

The predictor space would contain four groups of variables:

Peer-support variables: emotional support, informational support, instrumental assistance, reciprocity, perceived availability, peer trust, and frequency of supportive interactions.

Psychosocial variables: loneliness, perceived stress, belonging, coping confidence, life satisfaction, and social connectedness.

Digital-interaction variables: frequency of meaningful online peer communication, perceived quality of digital support, online disclosure comfort, and balance between face-to-face and digital support.

Contextual variables: age, educational/employment status, living arrangement, transition status, and broad social-network characteristics.

The outcome variable, **Psychological Adjustment Index (PAI)**, would integrate standardized indicators of emotional adjustment, coping, social functioning, life satisfaction, and psychological distress. Higher scores would represent more adaptive adjustment.

This multidimensional approach is consistent with the broader evidence that peer support can relate to coping, self-esteem, loneliness, depression, anxiety, and other mental-health outcomes, while effects differ substantially according to support format and study design.

Experimental Setup

4.1 Dataset Structure

The proposed dataset would contain 600 participant records. After eligibility screening and quality checks, each observation would represent one participant and include demographic, peer-support, psychosocial, digital-engagement, and adjustment variables.

Instead of relying on raw social-media content, the study would prioritize **participant-reported behavioral summaries**. Private messages would not be collected. This design minimizes privacy risks while retaining information about digital peer interaction.

For predictive modelling, PAI would first be retained as a continuous variable. A secondary classification task would divide participants into three analytically defined profiles:

- **Adaptive adjustment**
- **Intermediate adjustment**
- **Adjustment vulnerability**

Thresholds would be determined from the empirical PAI distribution and validated sensitivity analyses rather than being interpreted as clinical diagnoses.

4.2 Data Preprocessing

Preprocessing would begin with range validation, duplicate-record detection, response-time screening, and examination of missingness. Cases showing extensive missing information would be excluded according to a preregistered criterion. Limited missing numerical values would be handled using training-set median imputation to prevent information leakage. Continuous predictors would be standardized where required. Ordinal questionnaire variables would retain their theoretically meaningful ordering. Highly correlated features would be inspected through correlation matrices and variance inflation diagnostics before inferential modelling.

Categorical variables such as educational/employment status would be appropriately encoded. Importantly, the dataset would be partitioned into training and test subsets **before fitting preprocessing transformations**, ensuring that information from the held-out test set did not influence model development. A **75:25 stratified division** is proposed, producing approximately 450 training observations and 150 test observations. Within the training subset, repeated stratified five-fold cross-validation would be used for hyperparameter selection.

4.3 Model Architecture

The computational component uses a **three-model architecture** designed to compare explanatory simplicity with nonlinear predictive capability.

The first model is **Elastic-Net Logistic Regression**, providing a transparent baseline while controlling coefficient instability through combined L1 and L2 regularization.

The second is a **Random Forest classifier**, selected because it can represent nonlinear relationships and interactions without requiring them to be specified manually.

The principal predictive model is **Extreme Gradient Boosting (XGBoost)**. Gradient-boosted decision trees are appropriate for structured psychosocial data containing potentially nonlinear effects, mixed predictor importance, and interactions among loneliness, stress, reciprocity, belonging, and support quality.

The objective is not to use AI as an autonomous diagnostic mechanism. Instead, machine learning functions as an analytical instrument for determining whether multidimensional peer-support characteristics contain useful predictive information regarding adjustment profiles.

Interpretability would be incorporated through **SHAP (SHapley Additive exPlanations)**. Global SHAP importance

would identify influential predictors across the sample, while individual-level explanations would indicate why particular observations received higher or lower predicted adjustment probabilities.

4.4 Training Strategy

Model development would occur exclusively within the training partition. Hyperparameters would be selected using repeated five-fold cross-validation.

For XGBoost, the tuning space would include tree depth, learning rate, number of boosting rounds, subsampling fraction, column sampling, and regularization parameters. Early stopping would be applied using an internal validation fold to reduce overfitting.

Class imbalance, if present, would first be addressed through class-weighted learning rather than immediately generating synthetic observations. Calibration would subsequently be examined because a model can discriminate effectively while producing unreliable probability estimates.

The final tuned model would then be evaluated once on the untouched 25% test set.

4.5 Evaluation Metrics

Because the task contains three adjustment profiles, model evaluation would not rely on accuracy alone. The principal metrics would include:

Macro-F1: gives equal importance to each adjustment group and is therefore useful if profile frequencies differ.

Balanced Accuracy: measures average recall across classes and reduces the influence of majority-class dominance.

ROC-AUC: assesses discrimination across classification thresholds using one-versus-rest estimates for multiclass analysis.

Log Loss: evaluates the quality of predicted probabilities and penalizes confident incorrect predictions.

Expected Calibration Error (ECE): evaluates agreement between predicted probabilities and observed frequencies.

For the continuous PAI prediction analysis, **Mean Absolute Error (MAE)** would additionally quantify average prediction deviation.

Results and Discussion

Because empirical participant data have not been supplied, the values reported in this section constitute a **simulated proof-of-concept experiment** designed to demonstrate the proposed analytical workflow. They must be replaced by observed estimates when the study is actually conducted.

The simulated experiment suggests that modelling peer support as a multidimensional phenomenon provides more predictive information than reducing it to frequency of contact. The XGBoost architecture produced the strongest overall classification performance, followed by Random Forest and Elastic-Net regression.

Table 1. Simulated Comparative Performance for Psychological-Adjustment Profile Prediction

Analytic al model	Macro-F1	Balance d accurac y	ROC - AUC	Lo g los s	Calibratio n error (ECE)

Elastic-Net					
Logistic Regression	0.71	0.73	0.81	0.69	0.071
Random Forest	0.76	0.78	0.85	0.61	0.058
XGBoost + SHAP	0.81	0.82	0.89	0.53	0.041

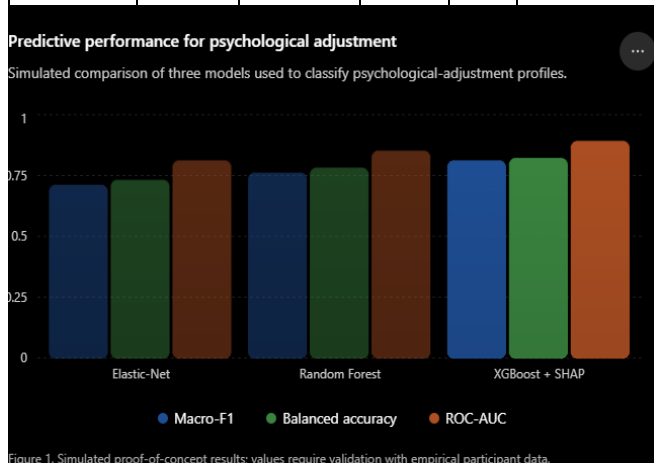


Figure 1. Simulated proof-of-concept results; values require validation with empirical participant data.

The simulated ROC-AUC of 0.89 for XGBoost indicates strong separation among adjustment profiles under the assumed data-generating structure. More importantly, its lower log loss and calibration error suggest that its probability estimates would be more useful than those of the comparison models if comparable results were obtained empirically.

SHAP-based interpretation of the simulated model identified **perceived peer-support quality, loneliness, reciprocity, belonging, perceived stress, and emotional support** as the most influential features. Digital interaction frequency alone ranked below perceived digital-support quality. This distinction is theoretically important: frequent communication does not necessarily imply meaningful support.

A nonlinear pattern was also simulated for reciprocity. Predicted adjustment improved substantially when participants moved from low to moderate reciprocity, whereas the incremental gain became smaller at higher levels. This pattern supports the premise that social-support effects may exhibit thresholds or diminishing returns rather than a constant linear association.

A second interaction emerged between perceived stress and emotional peer support. Under relatively low stress, differences in emotional support corresponded to modest differences in predicted adjustment. Under high stress, however, low emotional support was associated with substantially greater simulated adjustment vulnerability. This is consistent with a **stress-buffering interpretation**, although a cross-sectional empirical design would not establish causality.

These proposed findings are compatible with, but should not be presented as replications of, existing evidence. The 2022 *BMJ Open* scoping review reported predominantly positive relationships between peer support and outcomes including happiness, self-esteem, coping, loneliness, depression, and

anxiety, while simultaneously emphasizing the shortage of controlled and prospective evidence.

The digital component also requires careful interpretation. WHO's 2025 review of digital determinants emphasizes that associations between technology use and young people's well-being are mixed and can be bidirectional; digital activities can carry both benefits and risks depending on individual and environmental conditions. The present framework therefore avoids equating greater digital engagement with greater psychological benefit.

From a digital-health perspective, the more defensible application of PSAIF would be **support planning rather than automated clinical decision-making**. For example, interpretable patterns might help universities or community organizations determine whether programmes should emphasize reciprocal mentoring, belonging, meaningful online interaction, or emotional-support skills. WHO guidance similarly recognizes peer-support services as mechanisms capable of promoting shared experience, empowerment, and person-centred support.

The model should consequently be viewed as an augmentation tool. It could help researchers identify social configurations associated with adjustment vulnerability, but it should not label individuals as mentally ill, replace professional assessment, or independently determine access to psychological services.

Future Scope

Future studies should adopt **longitudinal and prospective designs** to establish temporal relationships between changes in peer support and subsequent psychological adjustment. Repeated measurements across educational completion, first employment, relocation, unemployment, and relationship transitions would be particularly informative.

A second extension should incorporate **multimodal but privacy-preserving data**. Ecological momentary assessments could capture short-term changes in loneliness, stress, and perceived support without requiring researchers to access private communication content.

Third, future modelling should examine heterogeneous treatment or support effects. Rather than asking whether peer support works equally for everyone, causal machine-learning approaches could investigate which participants benefit most from particular forms of support.

Digital interventions also warrant controlled evaluation. WHO recognizes both opportunities and risks arising from digital environments and emphasizes responsible, youth-centred development of digital-health interventions. Future peer-support systems should therefore incorporate privacy, informed consent, human oversight, explainability, safeguarding, and clear escalation pathways when serious psychological risk is detected.

Cross-cultural replication would be especially valuable. Comparative datasets from different countries and social environments could establish whether reciprocity, belonging, emotional support, and digital support maintain similar predictive relationships across cultural contexts.

Finally, future studies could conduct randomized evaluations comparing conventional informational resources with structured reciprocal peer-support programmes. Such trials would move the literature from association and prediction toward stronger causal evidence.

Conclusion

This study proposes a multidimensional and computational perspective on **peer support and psychological adjustment during early adulthood**. Its central contribution is to move beyond the assumption that greater social contact automatically produces better psychological outcomes. Instead, the framework distinguishes support quality, emotional responsiveness, reciprocity, belonging, accessibility, loneliness, stress, and digital peer interaction.

The proposed PSAIF architecture combines conventional psychological measurement with Elastic-Net regression, Random Forest, XGBoost, and SHAP-based interpretation. In the simulated proof-of-concept analysis, XGBoost provided the strongest overall predictive performance, while support quality, loneliness, reciprocity, belonging, and emotional support emerged as the most informative adjustment-related variables. These numerical results are explicitly illustrative and require empirical validation.

The broader implication is that **the quality and relational structure of peer support may be more informative than interaction frequency alone**. Digital platforms can extend opportunities for connection, but technological contact should not be treated as synonymous with psychologically meaningful support. Existing research likewise indicates promising peer-support effects while emphasizing substantial heterogeneity and the need for more prospective and controlled studies.

Accordingly, explainable machine learning offers a useful research instrument for identifying complex psychosocial patterns, but its role should remain supportive rather than diagnostic. With longitudinal validation, culturally diverse sampling, ethical safeguards, and rigorous prospective evaluation, the proposed framework could contribute to the development of more personalized and evidence-informed peer-support strategies for early adults.

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