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Leveraging Academic Library Services for Psychological Education Management: Enhancing Student Engagement and Mental Health

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Abstract

The rising prevalence of mental health challenges among students underscores the necessity of developing strategies that combine academic support with psychological education management. This research examined the contribution of academic library services to student interaction and psychological wellbeing. The Library-Assisted Psychological Education Management (LAPEM) approach represents a structured utilisation of library resources, encompassing digital collections, tailored learning materials, and interactive workshops, designed to enhance psychological education. LAPEM functions through data collection, where information on students' learning behaviours, library usage patterns, and psychological self-assessments is recorded. These datasets were processed using Z-score normalisation and winsorisation techniques. To address predictive needs, the study employed a deep learning (DL) architecture, specifically the Synergistic Fibroblast Fine-Tuned Single Hidden Layer Based Feedforward Neural Network (SF-SHL-FNN), aimed at estimating students' psychological risk levels and proposing appropriate interventions. The model incorporates adaptive feedback, enabling dynamic adjustment of library resource recommendations in line with students' changing requirements. An experimental evaluation with undergraduate participants revealed that students utilising LAPEM resources, particularly through tutoring, demonstrated greater academic engagement alongside reduced self-reported stress levels. Implementation using Python 3.10 achieved an accuracy rate of 0.962, suggesting that academic library services can operate as an effective, technology-driven mechanism for psychological education management. This framework offers a scalable and targeted intervention model, aligning educational resources with mental health support to simultaneously promote academic performance and emotional wellbeing.

Keywords: Academic Library Services, Psychological Education Management, Mental Health Support, Student Engagement, Synergistic Fibroblast Fine-Tuned Single Hidden Layer Based Feedforward Neural Network (SF-SHL-FNN).

Introduction

In recent years, there has been a noticeable increase in mental health concerns among university and college students (Prananto et al., 2025), highlighting the need for innovative interventions that balance both learning and wellbeing as priorities (Tang, 2021). Challenges such as stress, isolation, and academic pressure for both students and staff have intensified during the COVID-19 pandemic. Academic libraries, as central hubs for learning and knowledge dissemination, are positioned to play a significant role in addressing these challenges (Monnier et al., 2021; Mucherah and Ambrose-Stahl, 2014). By providing diverse resources, hosting interactive activities, and creating supportive environments, libraries help sustain student connections and reduce stress levels.

When complemented with psychological education, library services can further contribute to tailored support, enhancing both academic outcomes and mental health (Murphy et al., 2022). Many institutions have implemented library-based programmes that foster student interaction, emotional resilience, and holistic growth (Sun et al., 2016). Libraries also function as safe and structured environments where students can focus, study, and access guidance (Richard et al., 2022). Additionally, they facilitate workshops, collaborative learning, and access to digital platforms that promote academic and social engagement (Merga, 2020). These initiatives allow for personalised services that address students' academic, emotional, and social needs on a continuous basis (Kaufmann, 2021; Valdés-Cuervo et al., 2022). Findings indicate a strong association between academic library services and levels of engagement, learning behaviour, and psychological wellbeing among students. Previous studies employed models such as Random Forest, Random Forest + Text, Adaptive Boosting, k-Nearest Neighbour, and Naive Bayes (Abdul Rahman et al., 2023). However, these methods were constrained by limitations including small datasets, failure to integrate multiple behavioural indicators, and reduced predictive accuracy, which restricted their capacity to identify students at risk.

By comparison, the proposed Synergistic Fibroblast Fine-Tuned Single Hidden Layer Based Feedforward Neural Network (SF-SHL-FNN) model incorporates an extensive dataset that encompasses library usage, participation in workshops, behavioural indicators, and psychological metrics. This integration enhances predictive accuracy, sensitivity, and specificity. Visual analyses such as heat maps, scatter plots, and cumulative distribution graphs revealed that higher levels of library use and workshop engagement were linked to stronger learning behaviours and reduced psychological risks (Chong and Sin Soo, 2021). While traditional methods can process behavioural and text-based data to identify trends and provide personalised, evidence-based guidance to support academic progress and mental health, the SF-SHL-FNN model demonstrates more comprehensive predictive capacity. Overall, these approaches enable academic libraries to extend their role beyond resource provision, becoming active contributors to psychological education management through scalable and personalised interventions that nurture students' holistic development (Okyere-Kwakye and Md Nor, 2020; Pratiwi et al., 2022). Nevertheless, key challenges remain, including data heterogeneity, constraints in dataset size, ethical concerns over online data collection, variability in student and staff participation, and difficulties integrating such systems into library infrastructures to ensure usability for all stakeholders.

Research Objective

This study aims to explore the systematic integration of academic library services with digital and AI-based tools to promote students' psychological wellbeing, enhance their engagement, and deliver personalised support aimed at reducing stress and improving learning outcomes.

Research Contribution

- To establish a comprehensive framework that combines library services with psychological support, enabling students to manage stress, enhance engagement, and access personalised resources to support both academic performance and emotional wellbeing.
- To develop an intelligent predictive model (SF-SHL-FNN) capable of analysing student behaviour and patterns of library usage in order to assess psychological risk levels and propose targeted, evidence-based interventions.
- To evaluate the effectiveness of LAPEM in improving student outcomes by increasing engagement and reducing self-reported stress, thereby demonstrating a scalable approach for fostering holistic student development.

Research Organization

The study is structured to systematically examine the contribution of academic library services to enhancing student engagement and psychological wellbeing. Section 1 provides the introduction, presenting the background, rationale, and objectives for utilising library services in psychological education management. Section 2 reviews existing literature on student engagement, library utilisation, and mental health, identifying gaps in current research. Section 3 details the dataset, key variables, pre-processing techniques, and the analytical methodology employed. Section 4 presents the results through various visualisations. Section 5 discusses the implications of the findings for library-based interventions and situates them within the context of prior studies. Finally, Section 6 concludes the research, summarises its contributions, and outlines recommendations for future investigations.

Related Works

Zheng et al. (2024) examined the impact of the university library environment on learning engagement among college students, comparing liberal arts and science disciplines. The study utilised 45 university surveys to investigate library characteristics, peer interactions, and engagement levels. Results indicated that students in liberal arts exhibited lower learning engagement relative to their counterparts in science fields. Limitations of this study include its focus on specific institutions, the cross-sectional design which prevents causal inferences, and the restriction to only liberal arts and science majors. Brewster and Cox (2023) reviewed the implementation of a whole-university approach to student mental health in higher education institutions in 2017, evaluating both the analytical framework and the practicality of library involvement via national surveys and policy analysis. Findings highlighted that activities were largely locally driven, influenced by professional expertise and available resources, and were frequently framed in terms of wellbeing to enable preventive measures. A key limitation was the reliance on survey and policy data without longitudinal evidence to assess sustained effectiveness.

Knapp et al. (2023) explored the potential for integrating digital mental health (DMH) services in public libraries to support adolescents and underrepresented groups. The study employed interviews with 17 library staff to evaluate implementation and assessment frameworks. Findings indicated strong support for DMH integration, with safe spaces, community connections, and cost-free access to technology identified as principal strengths. Limitations included the small sample size, reliance on self-reported data, and focus on a single library setting. Shoaib et al. (2025) investigated how academic library spaces can foster student participation and learning in higher education. A structured questionnaire was administered to 212 sociology and economics students, with data analysed using Chi-Square tests and regression analysis. Results suggested that silent zones, creative spaces, and collaborative areas positively influenced student engagement. Constraints included the study's focus on a single institution, limited disciplines, and use of self-reported measures.

Cox and Brewster (2020) studied the role of academic libraries in promoting student mental health and wellbeing both before and during the COVID-19 pandemic. Survey results indicated that pre-pandemic initiatives were content-oriented, such as fiction collections, whereas during the pandemic, services focused on mitigating anxiety related to access to e-resources. While findings demonstrated a shift in service priorities, limitations included reliance on self-reported data, absence of longitudinal research, and context-specificity to the pandemic. Eccles and Wigfield (2020) aimed to address conceptual and theoretical gaps in Library and Information Science by developing a framework for student engagement in academic libraries. Qualitative data were collected via in-depth interviews across four libraries using flexible coding methods. The study produced a theoretical model outlining how student engagement can inform library planning, communication, and evaluation. Limitations involved the small sample and context-specific findings, restricting generalisability across diverse library systems.

Ifeyinwa and Umoh (2024) examined the roles of librarians and school counsellors in shaping student-focused libraries within technologically rich environments. Conceptually and exploratorily, the study revisited notions of librarianship, counselling, and student-centred learning. Findings highlighted that libraries are evolving into dynamic, student-focused spaces emphasising one-to-one learning and collaboration between librarians and counsellors. However, the study's descriptive nature and lack of empirical validation limit its broader applicability. Adeyanju et al. (2024) reported on the availability, awareness, and utilisation of AI tools in libraries and their effects on student learning. Survey data from 1,131 students indicated low awareness of advanced AI tools and limited usage compared with basic applications. The study found positive correlations between AI tool usage and learning outcomes, though gaps in digital literacy, infrastructure, and access to certain AI services were noted.

Nance (2022) highlighted the potential of play-based interventions in academic libraries to improve students' mental health. Practices examined included art supplies, video games, kinetic resources, and wellness activities such as colouring and crafting sessions. Results suggested these interventions could promote relaxation and improve mood under stress. Limitations included the absence of long-term outcome measures for mental health or engagement. Ali et al. (2022) conducted a SWOT analysis to examine AI adoption in university libraries, employing ethnographic interviews with five chief librarians. Findings suggested AI is gradually entering library services, offering opportunities for new services but raising concerns regarding resource and staff investments. The study was constrained by the small sample, qualitative approach, and lack of user perspective, indicating the need for broader empirical validation.

Lin et al. (2021) evaluated the effects of wearable spherical video-based virtual reality (SVVR) on cognitive load compared with map-based guides among students. A quasi-experimental design split participants into VR-guide and map-guide groups, with pre- and post-tests assessing knowledge acquisition. Results indicated that SVVR enhanced situational interest, engagement, stimulation, and learning outcomes. Limitations included short-term intervention, single-university setting, and small sample size, alongside reliance on self-reported measures without longitudinal assessment. O'Kelly et al. (2023) analysed eight years of data to examine correlations between library instruction and student outcomes, using consistent statistical methods and controlling confounding factors. Findings revealed that in-class library education positively correlated with re-enrolment, influencing programme modifications and faculty involvement. Limitations included the absence of causal inference and restriction to a single institutional context. Claunch et al. (2023) investigated the use of library-based escape rooms to enhance student engagement and participation in a cost-effective manner. Results demonstrated that escape rooms promoted collaboration, raised awareness of library resources, and positively affected student interest in library services. However, scalability challenges and the continual need to update content constrained broader implementation.

Research Gaps

Zheng et al. (2024) acknowledged that their study was confined to liberal arts and science majors and focused on specific institutions, with the cross-sectional design preventing causal inferences. The research did not account for the impact of digital or hybrid learning environments on engagement, nor did it include longitudinal analysis to capture evolving student-library interactions. Previous studies were also limited by small sample sizes and context-specific data derived from only four academic libraries, restricting their generalisability. Furthermore, Zheng et al. (2024) did not examine demographic or discipline-related differences that might influence various dimensions of student engagement across campuses. A promising approach to address these limitations is the application of the SF-SHL-FNN model, which has the capacity to integrate diverse contextual and behavioural data, enabling a more comprehensive analysis of student engagement.

Methodology

The LAPEM framework facilitates increased learning engagement and supports the psychological wellbeing of students. Data on student library usage, interests, and self-reported stress levels were collected and pre-processed to ensure consistency. Key features reflecting both behavioural patterns and psychological status were identified. The framework incorporates a neural network model (SF-SHL-FNN) designed to predict students' psychological risk levels and recommend suitable library resources accordingly. The effectiveness of the framework was evaluated using engagement and stress as primary indicators. The procedural flow of the proposed methodology is illustrated in Fig. 1.

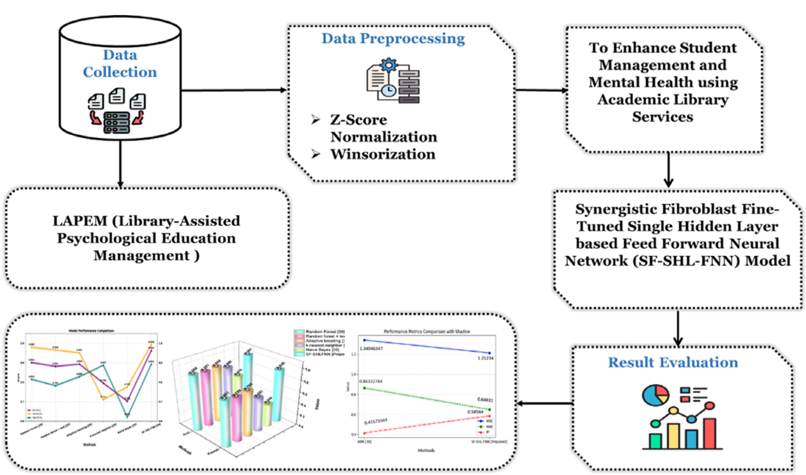


Figure 1: Proposed Framework.

Data Collection

The dataset was obtained from the Kaggle repository (Kaggle, n.d.). It encompasses information on student engagement, academic resource utilisation, and psychological indicators, enabling the examination of relationships between library services and mental health. The dataset includes variables such as weekly hours spent in the library, scores for digital resource usage, attendance at interactive workshops, learning behaviour scores, self-reported stress levels, and satisfaction with library resources. A derived variable, Psychological_Risk_Level (ranging from 0 to 100), provides an estimate of students' mental wellbeing risk based on these factors. Key features, including Hours_in_Library_per_Week, Digital_Resource_Usage_Score, Interactive_Workshop_Attendance, Learning_Behavior_Score, Self_Reported_Stress_Level, and Library_Resource_Satisfaction, offer multidimensional insights into student behaviour. This dataset can be utilised to analyse correlations between academic engagement and mental health, identify students at risk, and inform strategies aimed at enhancing both learning outcomes and psychological wellbeing.

Data Pre-Processing

The collected student data, including behavioural patterns, interactions, and self-reported stress observations, were prepared to ensure reliability and validity. To mitigate the influence of extreme values, the dataset was normalised using Z-score normalisation and Winsorisation techniques. This pre-processing step supported the development of the LAPEM framework, which aims to enhance student engagement, monitor psychological wellbeing, and provide personalised interventions. Following pre-processing, the data were analysed using the SF-SHL-FNN model to predict students' psychological risk levels and deliver adaptive, individualised library-based interventions.

Z-Score Normalization

Z-score normalisation is a pre-processing technique that standardises data by converting values relative to their mean and standard deviation. This method ensures that all features are scaled consistently, preventing bias during model training. In this study, the primary objective is to optimise library services to enhance both student engagement and psychological wellbeing. Z-normalisation plays a crucial role in preparing student data, encompassing library usage and psychological indicators. By reducing discrepancies and balancing feature scales, it enables the SF-SHL-FNN model to efficiently recognise patterns, thereby producing reliable outcomes for managing academic libraries as environments that support students' mental health. Equation (1) formally defines the normalisation process.

$$W_{new} = \frac{W-\mu}{\sigma} = \frac{W-Mean(W)}{StdDev(W)} \quad (1)$$

Where, W represents the original data value, $\boldsymbol{\mu}$ is the mean of the dataset, and $\boldsymbol{\sigma}$ is the standard deviation.

Winsorization

Winsorisation is a statistical technique used to adjust values identified as outliers—those at the extreme high or low percentiles—rather than removing them entirely from the dataset. This approach preserves the full sample size and optimises its utilisation, reducing the risk that outliers might distort analysis or predictive modelling. In the context of student engagement and psychological assessment, Winsorisation is applied to variables such as library hours, digital resource usage, and stress measures, ensuring that extreme or atypical behaviour does not skew observed trends or correlations. By focusing on representative student patterns, Winsorisation enhances the reliability of the analysis, supporting the research objective of using academic library services to manage psychological education, increase student participation, and promote psychological wellbeing. Equation (2) formally illustrates the Winsorisation process.

$$x(q_s) = \begin{cases} -u & For\ q_s \leq -u \\ q_s & For\ |q_s| < u \\ u & For\ q_s \geq u \end{cases} \quad (2)$$

The variable $x(q_s)$ represents the Winsorized value of the original data point q_s, which could correspond to metrics such as student engagement, library usage, or self-reported stress levels The parameter u represents a positive threshold that establishes the upper and lower bounds for the Winsorization process.

Forecast the Level of Psychological Risk of Students using Hybrid SF-SHL-FNN

The SF-SHL-FNN is a hybrid deep learning model designed to predict students' psychological risk levels and provide personalised interventions, aligning with the research objective of utilising academic library services to enhance engagement and psychological wellbeing. The model incorporates a single hidden layer to capture complex patterns within students' behavioural and psychological data, including variables such as library access, engagement rates, and self-reported stress levels. It employs a synergistic fibroblast-like mechanism to optimise network weights, improving learning efficiency and generalisation even with small or noisy datasets. By enhancing the traditional feedforward neural network architecture and integrating this optimisation process, the SF-SHL-FNN model enables precise risk prediction and supports library-based interventions, offering a scalable and adaptive framework to promote both academic performance and psychological wellbeing.

SHL-FNN

The SHL-FNN is a single-layer neural network that processes input features to identify underlying relationships within the data. Within the LAPEM framework, it utilises information on students' library usage, frequency of engagement with library facilities, and self-reported stress levels to detect behavioural patterns and predict the extent of psychological risk faced by students.

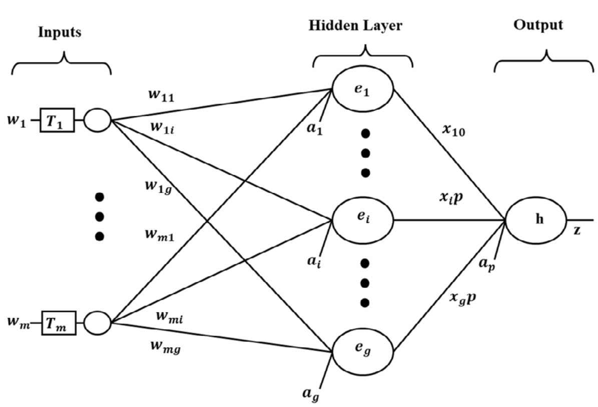


Figure 2: Single Hidden-Layer Feed Forward Neural Network.

The feedforward architecture, illustrated in Fig. 2, allows information to flow unidirectionally from input to output, ensuring efficient learning and straightforward implementation. When combined with the fine-tuning mechanisms, the SHL-FNN delivers accurate and adaptable predictions, enabling the provision of personalised interventions as defined in Eqs. (3) and (4).

$$z = h\left[a_p + \sum_{i=1}^{g} x_i p u_i\right] \quad (3)$$

$$u_i = e_i + \left[a_i + \sum_{j=1}^{m} x_{ji}\, t_j w_j\right] \quad (4)$$

In the above Equations (3) and (4), h represents the hidden layer output, while a_p denotes the activation parameter. The term x_i corresponds to the i - th input feature, p indicates the connection weight. The transformed input signal is denoted by u_i, which incorporates the error adjustment term e_i along with the bias parameter a_i Furthermore, x_{ji} represents the j - th feature associated with the i - th neuron, where t_j acts as the transfer function coefficient, w_j denotes the synaptic weight, and g is the count of input features, is the number of contributing factors or parameters in the secondary summation over j. Z is the output signal or predicted response of the model neuron.

SF

The Synergistic Fibroblast (SF) functions as the fine-tuning mechanism within the neural network, enhancing learning through dynamic adjustments of network weights inspired by the behaviour of fibroblast-like neurons. This mechanism improves the generalisability of the model, allowing more accurate prediction of psychological risk. Neural networks incorporating the SF mechanism are capable of capturing variations in behavioural and engagement data, facilitating adaptive and individualised interventions and making the network more responsive to students' needs. Equation (5) formally represents the SF formulation.

$$u^{j(s+1)} = u^j(s) + (1-\rho)d\left(e^j(s), s\right) + \rho * \frac{e^j(s+\tau)}{\|e^j(s-\tau)\|} \quad (5)$$

Where, $u^{j(s+1)}$ represents the updated state or position of agent j at iteration s + 1, while uj (s) denotes its current state at iteration . The term ρ is a weighting factor that balances the influence of the local adjustment and the delayed evaluation. The function $d(e^j(s), s)$ defines the directional adjustment based on the agent's current evaluation $e^j(s)$, which corresponds to its objective function or performance measure. The parameter represents a time-delay step, allowing the equation to incorporate past or future states, and e^j (s – τ) is the norm of the evaluation at the delayed iteration, used to normalize the delayed contribution in the update process. Algorithm 1 defines the combined model of SF-SHL_FNN.

Algorithm 1: Hybrid SF-SHL-FNN

Input: Student data X = [x1,x2, …, xn] // features: library usage, engagement, stress

Output: Predicted psychological risk level and recommended intervention

Initialize:

- *SHL-FNN weights W and biases a randomly*
- *Learning parameters: ρ,τ*
- *Error term e*

For each iteration s = 1 to MaxIterations:

For each student j in dataset:

// SHL-FNN forward pass

hidden_output = SHL_FNN_forward(X, W, a) // single hidden layer transformation

predicted_risk = compute_output(hidden_output)

// Calculate prediction error

e_j = evaluate_error(predicted_risk,actual_value)

// Synergistic Fibroblast fine-tuning

If e_j > high_threshold:

adjustment = strong_update(e_j, ρ, τ)

Else if e_j < low_threshold:

adjustment = minor_update(e_j,ρ,τ)

Else:

adjustment = moderate_update(e_j, ρ, τ)

// Update SHL-FNN weights and biases

*W = W + learning_rate * adjustment*

*a = a + learning_rate * adjustment*

// Recommend intervention based on risk

If predicted_risk > high_risk_threshold:

intervention = "Immediate counseling + high engagement resources"

Else if predicted_risk > medium_risk_threshold:

intervention = "Moderate support + library engagement program"

Else:

intervention = "Routine library guidance"

Return predicted_risk, intervention

The SHL-FNN-based LAPEM algorithm estimates students' psychological risk levels by analysing their engagement, library utilisation, and self-reported stress through a single hidden layer feedforward neural network. Network weights are fine-tuned using the Synergistic Fibroblast mechanism, and personalised interventions are suggested according to the predicted risk. The algorithm enables identification of individual students' psychological risk based on library engagement and behavioural data, allowing tailored measures to enhance both engagement and mental wellbeing. In this context, X denotes the feature vector representing student data—including library usage, engagement, and stress levels—while

W represents the weight matrix of the SHL-FNN.

Result

Using Python 3.10, the analysis of student learning behaviours was conducted to assess the impact of library engagement on both academic performance and psychological wellbeing. The proposed SF-SHL-FNN model demonstrated superior performance compared with existing models, achieving an accuracy of 0.962, sensitivity of 0.993, specificity of 0.892, kappa of 0.920, area under the curve (AUC) of 0.981, and an R^2 of 0.58564. Error metrics, including mean squared error (MSE) of 1.21234 and mean absolute error (MAE) of 0.64831, were comparatively low, indicating that the proposed model provides precise detection of student engagement and mental health outcomes.

Correlation Heatmap

Figure 3 illustrates the intensity and co-occurrence of different learning behaviours among students, with darker regions indicating stronger interactions and correlations. The SF-SHL-FNN-based LAPEM algorithm analyses these behavioural patterns to predict psychological risk levels and suggest targeted interventions. This visualisation highlights how recognising such patterns, in conjunction with utilising academic library services for psychological education management, can improve student engagement and foster mental wellbeing.

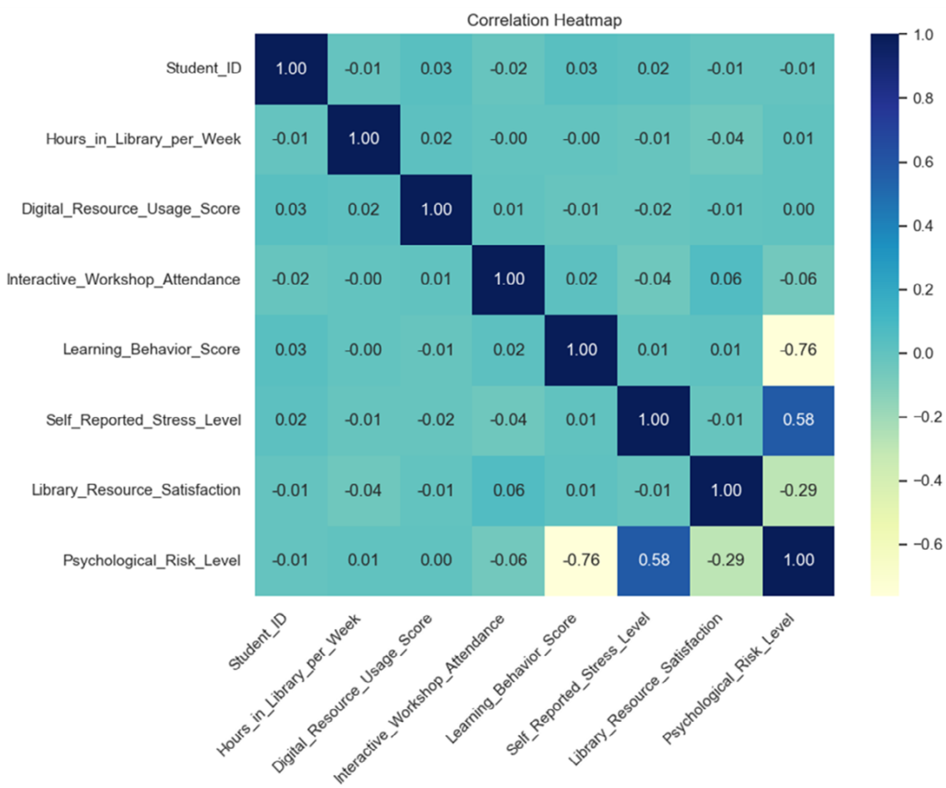


Figure 3: A Graphical Representation of the Heatmap of Behavioural Interactions.

Library Hours vs Learning Behaviour Score

Figure 4 depicts the relationship between the duration of students' library visits and their corresponding learning behaviour scores, with each point representing an individual student's engagement level. This visualisation facilitates the identification of trends and patterns in student learning behaviours. The findings further corroborate the efficacy of the proposed SF-SHL-FNN-based LAPEM algorithm, which analyses student data—including library usage, engagement, and stress levels—to predict psychological risk and provide personalised interventions. Figure 4 highlights the potential of academic library resources to enhance student participation, awareness, and the management of psychological wellbeing.

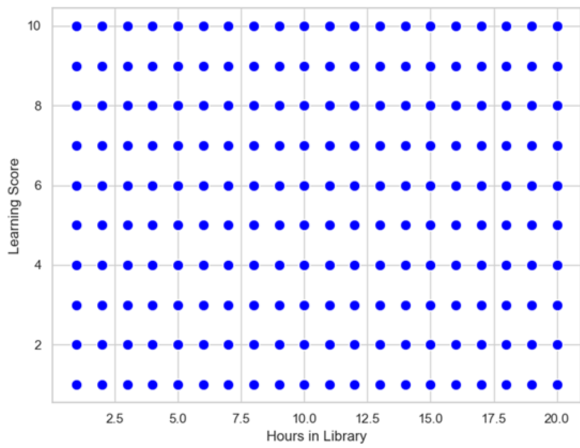


Figure 4: A Graphical Representation of Learning Hours' vs Behaviour Score.

Error Bar Plot of Behavioural Scores

Figure 5 presents the mean predicted psychological risk levels and corresponding recommended interventions for various student groups, as determined by the SF-SHL-FNN-based LAPEM algorithm. The figure highlights variability and confidence intervals in risk predictions, enabling comparison across groups to identify students at risk. This analysis provides a quantification of engagement and mental wellbeing indicators, informing targeted interventions that utilise library services. The visualisation supports educators and librarians in developing personalised strategies to enhance both student learning outcomes and psychological wellbeing.

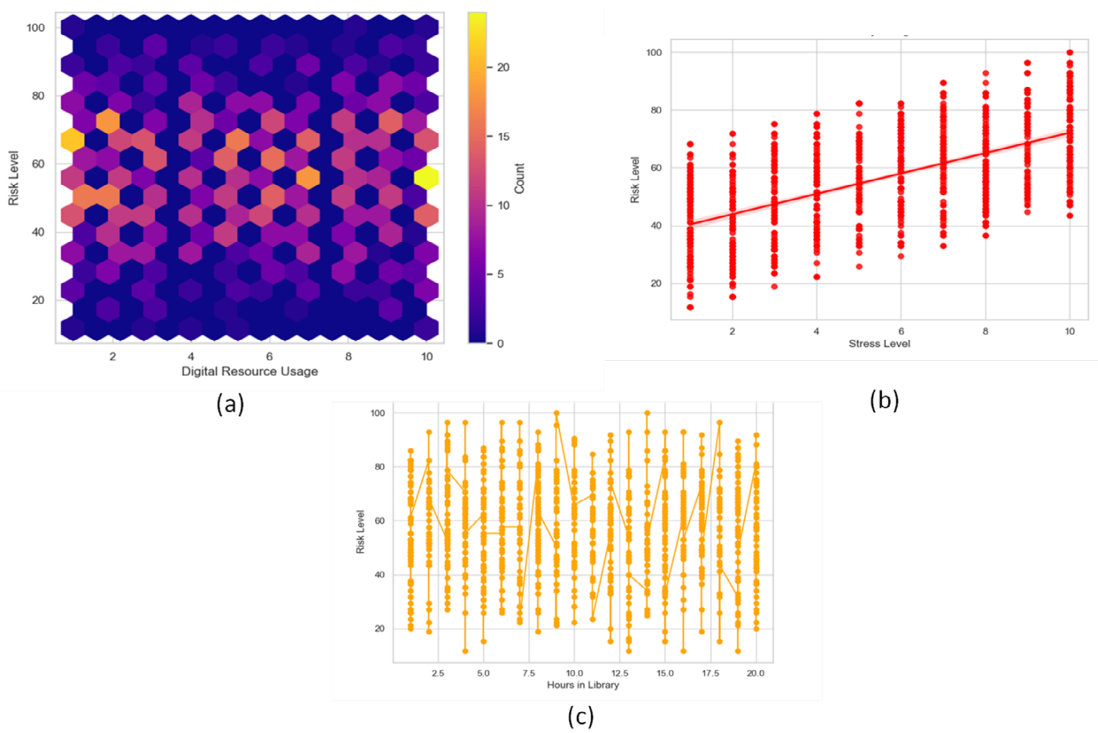
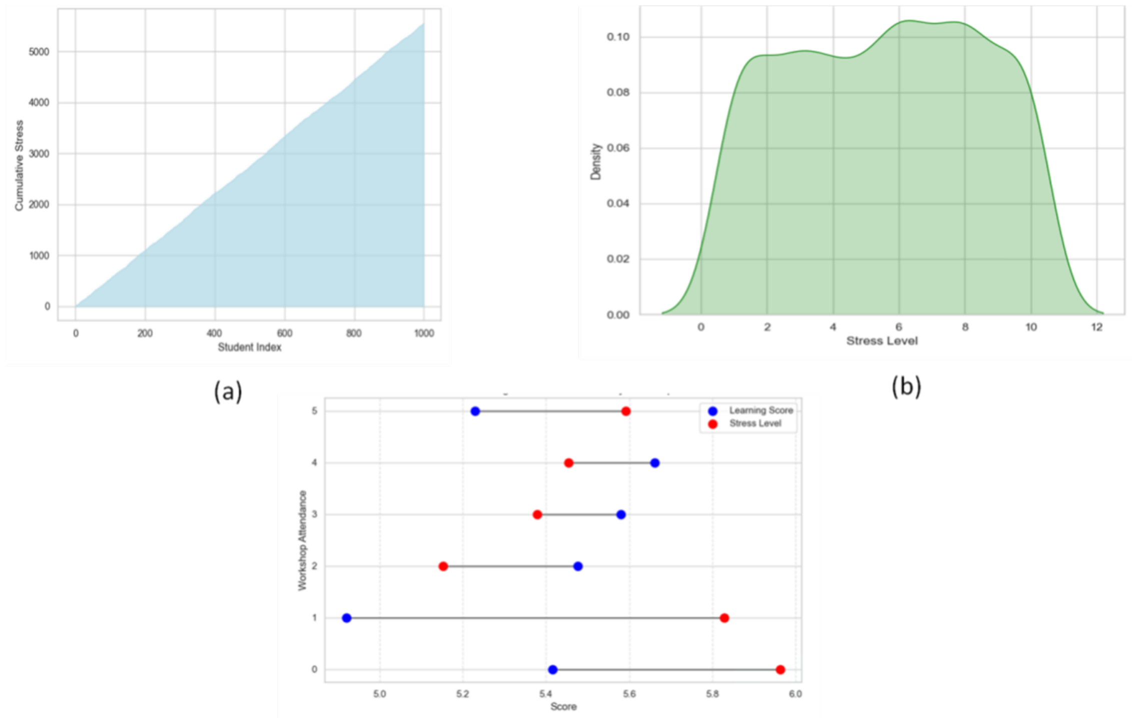


Figure 5: Representation of (a) A Graphical Representation of Digital Resources vs Risk Level (b) Psychological Stress Level (c) Risk Level vs Hours in Library.

Cumulative Density Function & Distribution Plot

Figure 6 depicts the cumulative probability distribution of predicted psychological risk levels produced by the SF-SHL-FNN-based LAPEM algorithm. This visualisation facilitates the determination of thresholds and percentile-based assessments, allowing for the identification of high-risk or high-performing students. It underpins library-driven psychological education strategies aimed at improving both mental health and learning outcomes. Additionally, it enables educators and librarians to track engagement and risk trends over time, develop personalised interventions, and make data-driven decisions to optimise library services for the enhancement of academic performance and psychological wellbeing.

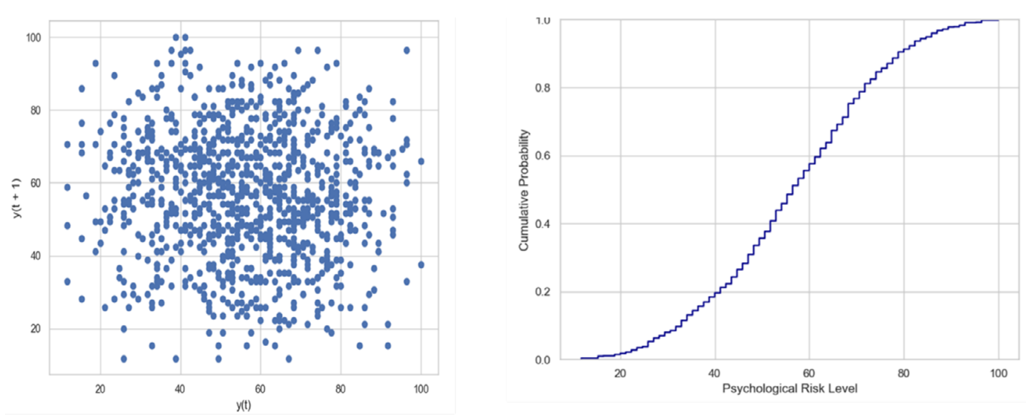


(c)

Figure 6: Outcomes of (a) A Graphical Representation of Cumulative Stress Level (b) Density of Stress Level (c) Dumbbell Plot.

Pair Plot of Behavioural Variables

Figure 7 illustrates the distributions and interrelationships among multiple behavioural metrics using scatter plots and histograms, with the data processed through the SF-SHL-FNN-based LAPEM algorithm. The visualisation highlights multivariate dependencies among student behaviours, revealing patterns and anomalies that support the identification of engagement trends across the student population. By understanding these relationships, library-driven interventions can be optimised to enhance learning outcomes and psychological wellbeing. Utilising academic library services through LAPEM for psychological education management, this visualisation assists educators in designing evidence-based programmes and monitoring the effectiveness of targeted interventions to improve student engagement.



(a) (b)

Figure 7: Outcomes of (a) A Graphical Representation of the Log Plot of Psychological Risk Level (b) ECDC of Psychological Risk Level.

Graph Based on Risk Category

Figure 8 presents the proportion of students demonstrating specific categories of learning behaviour, with predictions produced by the SF-SHL-FNN-based LAPEM algorithm. The visualisation highlights predominant behaviours as well as potential gaps in engagement, informing targeted psychological education strategies. It facilitates the design of library-based programmes aimed at promoting positive behaviours, enhancing mental wellbeing, and improving student engagement. Furthermore, it assists educators in identifying behaviours requiring focused interventions, optimising the allocation of library resources, and tracking progress over time to evaluate the effectiveness of library-supported psychological education initiatives.

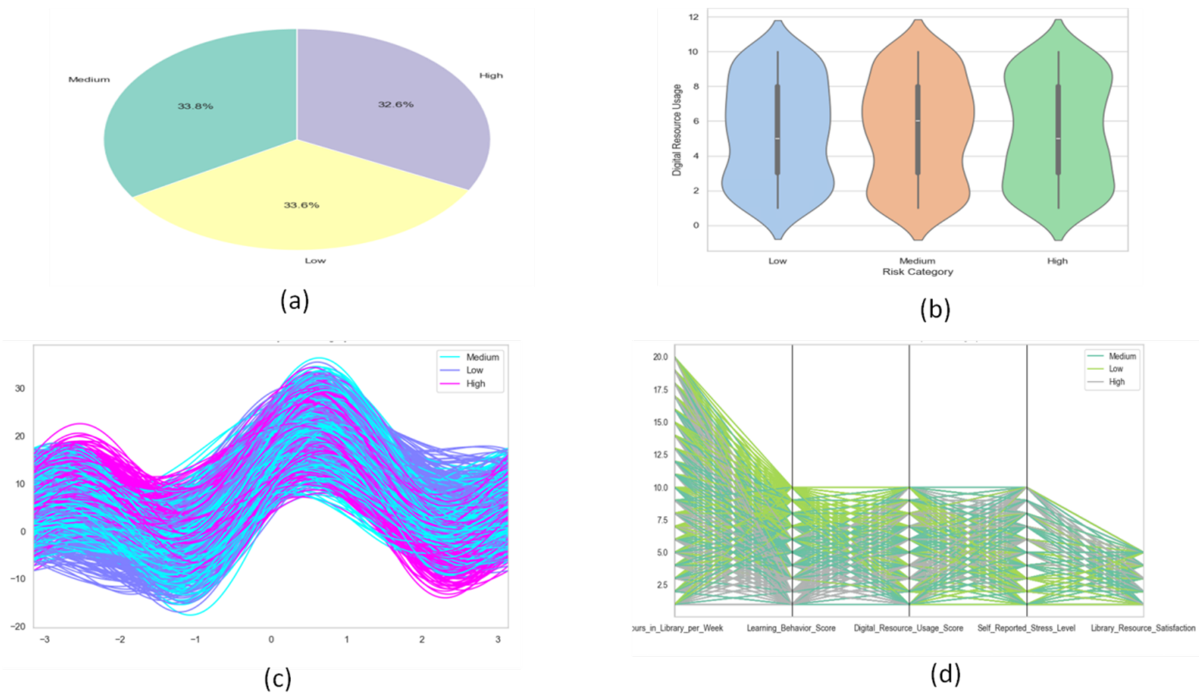


Figure 8: Representation of (a) A Graphical Representation of the Proportion of Students by Risk Category (b) Digital Resource usage by Risk Category (c) Andrews Curves by Risk Category (d) Parallel Coordinates by Risk Category.

Comparison Metrics

A comparative analysis was conducted between conventional methods and the proposed SF-SHL-FNN approach, including Random Forest (Abdul Rahman et al., 2023), Random Forest + Text, Adaptive Boosting, k-Nearest Neighbour, Naive Bayes, and conventional ANN (Khan et al., 2024). A deep learning variant using an artificial neural network (ANN) was employed as a benchmark model, as it is capable of capturing non-linear relationships within student data. The SF-SHL-FNN consistently demonstrated superior predictive performance and robustness across all evaluation metrics, including accuracy, kappa, sensitivity, specificity, AUC, MSE, MAE, and R^2. These results clearly indicate the advantage of the proposed fine-tuned single hidden layer architecture over traditional approaches and conventional ANN models.

Accuracy

Accuracy is a performance metric that quantifies the proportion of correctly classified outcomes relative to the total number of predictions, as defined in Eq. (6). An accuracy of 0.962 indicates the effectiveness of the SF-SHL-FNN-based LAPEM algorithm in predicting student engagement levels and psychological risk by utilising academic library services for psychological education management. The algorithm analyses student data—including library usage, engagement, and stress indicators—through a single hidden layer feedforward neural network enhanced with Synergistic Fibroblast fine-tuning, producing personalised risk predictions and corresponding interventions. Table 1 and Figure 9 illustrate the accuracy of the proposed approach.

$$Accuracy = \frac{TP+TN}{FP+FN+TP+TN} \quad (6)$$

In this context, TP and TN represent true positive and true negative outcomes, respectively, while FP and FN denote false positive and false negative outcomes.

Sensitivity

Sensitivity, also referred to as recall or the true positive rate, quantifies the proportion of actual positive cases correctly identified by a model, as defined in Eq. (7). In the present study, the SF-SHL-FNN-based LAPEM algorithm detects students at risk by analysing variables such as library usage, learning behaviours, and stress indicators. The high sensitivity of 0.993 enables timely delivery of interventions to support students' wellbeing. Table 1 and Figure 9 present the corresponding metrics for the proposed approach.

$$Sensitivity = \frac{TP}{TP+FN} \quad (7)$$

Specificity

Specificity, also known as the true negative rate, quantifies the proportion of actual negative instances correctly identified by a model, as defined in Eq. (8). In this study, the SF-SHL-FNN-based LAPEM algorithm assesses its ability to recognise students who are not at risk or exhibit lower engagement levels, based on factors such as library usage and learning behaviours. A high specificity of 0.892 ensures that students not requiring interventions are accurately identified, supporting strategies aimed at optimising engagement and psychological wellbeing through academic library services for psychological education management. Table 1 and Figure 9 illustrate the specificity results.

$$Specificity = \frac{TN}{TN+FP} \quad (8)$$

Table 1: Performance Comparison of Classification Methods with Existing Models.

Methods	Accuracy	Sensitivity	Specificity
Random Forest	0.901	0.980	0.815
Random Forest + Text	0.881	0.965	0.782
Adaptive Boosting	0.893	0.951	0.828
K-Nearest Neighbour	0.795	0.711	0.887
Naïve Bayes	0.702	0.775	0.621
SF-SHL-FNN [Proposed]	0.962	0.993	0.892

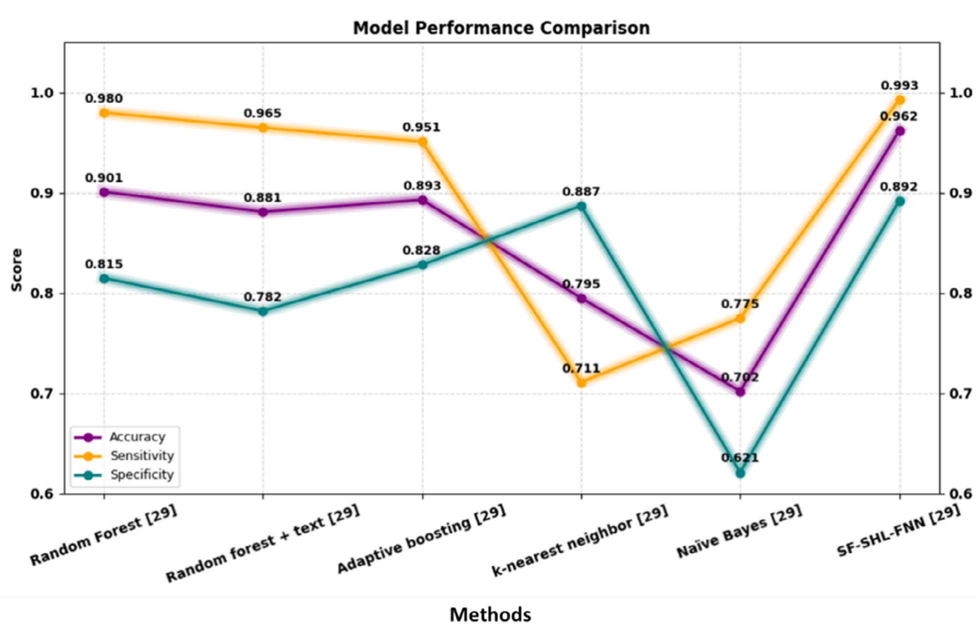


Figure 9: A Graphical Representation of Suggested Metrics.

Kappa

Cohen's Kappa (κ) quantifies the agreement between model predictions of student engagement or psychological risk and the actual observations, taking into account the level of agreement expected by chance, as defined in Eq. (9). The SF-SHL-FNN-based LAPEM algorithm exhibits a high Kappa value of 0.920, indicating strong reliability in accurately identifying students who are at risk or highly engaged. This supports the utilisation of academic library services for psychological education management, contributing to improved student engagement and mental wellbeing outcomes. Table 2 and Figure 10 present this metric.

$$\kappa = \frac{P_o - P_e}{1 - P_e} \quad (9)$$

Where, P_o = Observed agreement between predictions and actual labels, P_e = Expected agreement by chance, k =Kappa.

Area Under Curve (AUC)

The area under the receiver operating characteristic (ROC) curve (AUC) quantifies the model's ability to discriminate between categories. In this study, the SF-SHL-FNN-based LAPEM algorithm evaluates its capacity to differentiate students at risk of psychological difficulties from those who are not, based on engagement and library usage data. A high AUC of 0.981 indicates strong discriminative power, demonstrating that the model can reliably identify students requiring interventions. This aligns with the objective of leveraging academic library services for psychological education management to enhance both student engagement and mental wellbeing. Table 2 and Figure 10 illustrate the corresponding metrics.

Table 2: Analysis of Kappa and AUC.

Methods	Kappa	AUC
Random Forest	0.801	0.966
Random Forest + Text	0.759	0.951
Adaptive Boosting	0.785	0.959
K-Nearest Neighbour	0.593	0.886
Naïve Bayes	0.399	0.678
SF-SHL-FNN [Proposed]	0.920	0.981

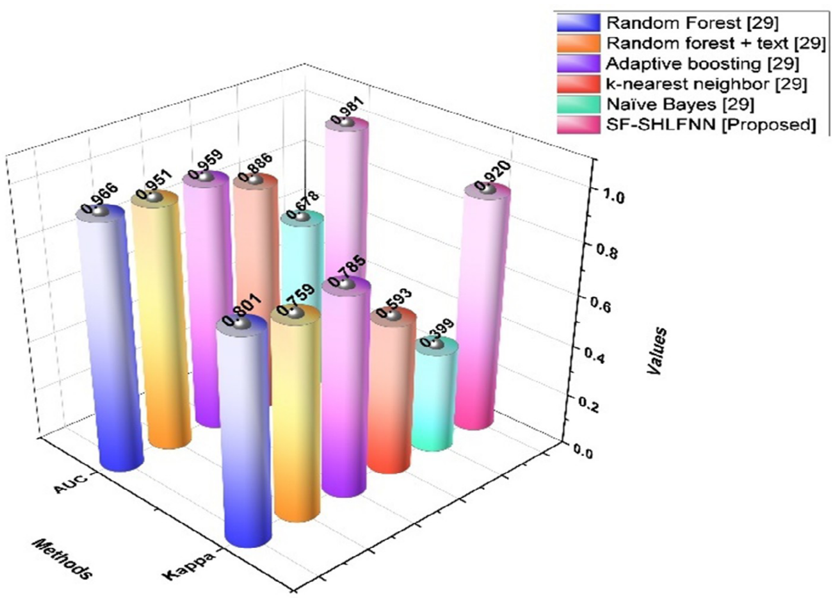


Figure 10: A Graphical Representation of the Given Metrics.

MSE

The MSE quantifies the average squared difference between predicted and actual values, as defined in Eq. (10). In this study, the SF-SHL-FNN-based LAPEM algorithm evaluates its ability to accurately predict student outcomes, including learning behaviour scores and levels of psychological risk, based on library usage and engagement data. A lower MSE of 1.21234 indicates higher predictive performance, demonstrating that the model's estimates closely align with observed values. These results support the use of academic library services as an effective tool for psychological education management, contributing to improved student engagement and mental wellbeing.

$$MSE = \frac{1}{m}\sum_{k=1}^{m}(\hat{x_i} - x_i)^2 \quad (10)$$

Where m is the total count of observations,

$\widehat{x_i}$ is the estimated value of i - th observation, x_i is the actual value of i - th observation, and k is the number of observations. MSE quantifies the mean squared residuals between predicted and actual values, providing a numerical measure of prediction accuracy while assessing student engagement and supporting mental health outcomes. Table 3 and Figure 11 illustrate the MSE results.

MAE

MAE quantifies the mean absolute difference between predicted and actual values, as defined in Eq. (11). Expressed in the same units as the original data, it provides a clear measure of prediction accuracy. In this study, the SF-SHL-FNN-based LAPEM algorithm attains a low MAE of 0.05432, demonstrating that the model produces accurate and reliable estimates of student engagement and psychological support outcomes.

$$MAE = \frac{1}{t}\sum_{j=1}^{t} y_i - \widehat{y_i} \quad (11)$$

Where y_i represents the actual value of the i - th student observation, such as learning behaviour score or psychological risk level, while y_i denotes the corresponding predicted value generated by the model. The total number of observations is denoted by . A low MAE of 0.64831 indicates that the model's predictions closely correspond to the actual values, reflecting high accuracy. This metric is particularly valuable for assessing the effectiveness of the model in predicting student engagement and mental wellbeing outcomes. Table 3 and Figure 11 illustrate the MAE results.

R^2

R^2 quantifies the proportion of variance in the dependent variable that can be explained by the independent variables. In this study, the SF-SHL-FNN-based LAPEM algorithm evaluates its ability to capture variations in student outcomes, including learning behaviour scores and psychological risk levels, based on library engagement and other behavioural indicators. An R^2 value of 0.58564 reflects strong predictive performance, demonstrating the model's effectiveness in utilising academic library services to enhance student engagement and mental wellbeing. Table 3 and Figure 11 present the MSE, MAE, and R^2 metrics.

Table 3: Analysis of MAE, MSE and R^2.

Methods	MSE	MAE	R^2
ANN	1.34046347	0.86322784	0.41575944
SF-SHL-FNN [Proposed]	1.21234	0.64831	0.58564

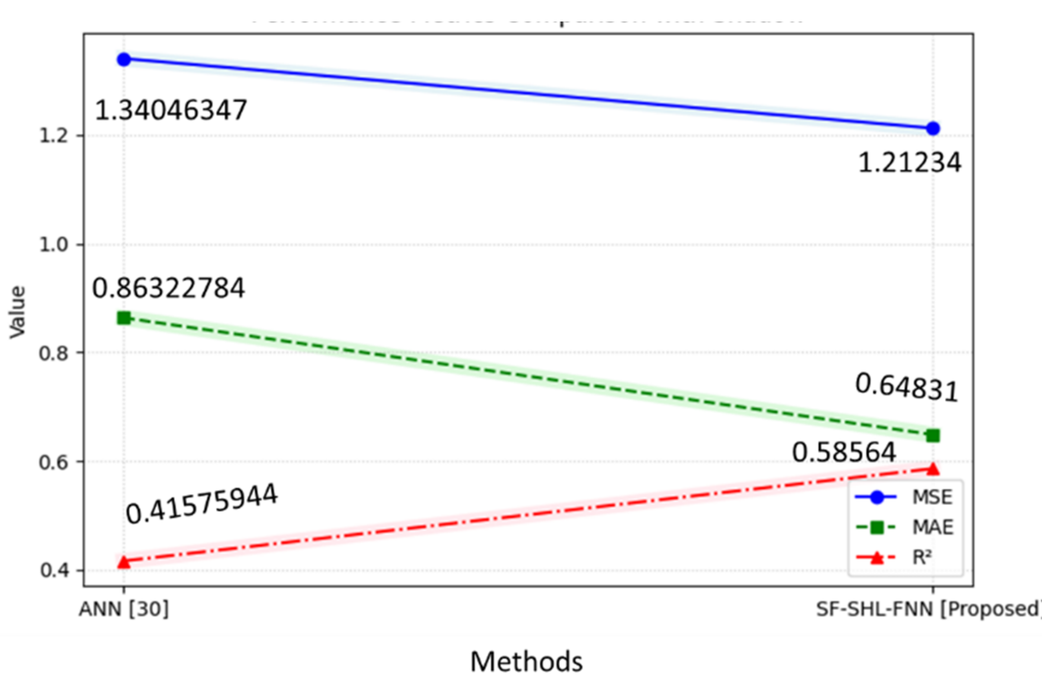


Figure 11: A Graphical Representation of MAE, MSE and R^2.

Discussion

The findings indicate a strong association between academic library services and student engagement, learning behaviour, and psychological wellbeing. Previous studies have employed methods such as Random Forest, Random Forest + Text, Adaptive Boosting, k-Nearest Neighbour, and Naive Bayes (Abdul Rahman et al., 2023), yet these approaches were constrained by limited dataset sizes, insufficient consideration of multiple behavioural indicators, and lower predictive accuracy, which restricted their capacity to effectively identify at-risk students. By contrast, the proposed SF-SHL-FNN model leverages a comprehensive dataset encompassing library usage, workshop attendance, learning behaviour, and psychological indicators, thereby achieving enhanced accuracy, sensitivity, and specificity. Visual analyses, including scatter plots, heat maps, and cumulative distribution plots, reveal that higher library engagement and workshop participation correlate with elevated learning behaviour scores and reduced psychological risk levels.

Conclusion

The research confirms the efficacy of utilising academic library services within psychological education management to improve student engagement and mental wellbeing. Application of the SF-SHL-FNN model enabled the prediction of student learning behaviours and psychological risk with an accuracy of 0.962, a sensitivity of 0.993, and a specificity of 0.892, surpassing conventional approaches. Performance metrics, including R^2 (0.58564), MAE (0.64831), and MSE (1.21234), substantiate the model's predictive capability, while AUC (0.981) and Kappa (0.920) demonstrate classification reliability. Visualisations and correlation analyses indicate that increased library utilisation and workshop attendance are strongly linked with enhanced learning engagement and reduced psychological risk. Collectively, these findings underscore that targeted, library-based interventions informed by behavioural analytics and predictive modelling can substantially improve student learning outcomes and support mental wellbeing, emphasising the pivotal role of academic libraries in psychological education management.

Limitations and Future Scope

The study's limitations include a relatively small sample size, a short-term evaluation period, and reliance on self-reported measures. Future research should focus on larger and more diverse student populations, extend the temporal scope to assess long-term effects, integrate LAPEM with campus-wide mental health services, and enhance the predictive model through the application of advanced AI techniques to enable real-time, individualised interventions.

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