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A Multi-Method Statistical and Machine Learning Analysis of Living Arrangements and Student Mental Well-being

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ABSTRACT: Mental health among students is an emerging issue in the tertiary education sector, as it relies on academic, social and environmental factors. This study examines the potential effects of living arrangements on student mental health using a multi-method analytical framework. The recommended approach includes the use of descriptive statistics, inferential test, Structural Equation Modeling (SEM), Bayesian inference, time series analysis, and machine learning techniques. Results have shown statistically significant differences in living conditions ($p < 0.05$) such that living independently is associated with higher anxiety and social isolation. SEM shows social isolation (= -0.52) to be the most predictive of mental well-being and the second strongest predictor, then financial stress (= -0.36). Accuracy of machine learning models up to 88 bets on the credibility of forecasts. The framework offers a data-driven and scalable method of comprehending, anticipating, and enhancing student mental health The Random Forest model achieved a predictive accuracy of 88.3%, demonstrating strong predictive performance for student mental well-being classification.

1. INTRODUCTION

The mental health of students has become one of the most acute problems of the higher education system of the last several years. The academic workloads, social transitions and financial pressures usually subject the university students to increased stress, anxiety and depressions. Studies have still served to point out that mental health related issues among the students have only continued to escalate tremendously over the past decade [1].Living arrangement, either by living with the family, staying in the university hostels and dormitories or single living, conditions each of the environment that affect the student mental health. All types of living conditions provide different levels of social support, financial responsibility and fair permanence of the lifestyle, which can directly affect psychological deliverables. Indicatively, students living outside family setups have a higher probability of reporting to have experienced higher levels of loneliness and emotional distress but that supportive social atmospheres might improve the magnitude of resilience and wellness. It is also due to COVID-19 that the importance of living conditions came to the fore, as changes in accommodation and social isolation related to COVID-19 more strongly affected the mental health of students. Subsequently, more attention has been paid to using statistical and computational techniques to determine the correlation between living conditions and psychological health. Popular in traditional methodologies, group differences are often desired to establish predictors of mental health outcomes. Descriptive statistics, ANOVA, and regression analysis have been popular in traditional methods. More recent developments have created parametric tests, Structural Equation Modelling (SEM), Bayesian as well as machine learning to process more complex pattern of data and improve the accuracy of predictions [2].The interplay of environmental, social and financial determinants is complex in relation to the mental well-being of students. Current literature is mostly based on one method of analysis, e.g., statistical analysis, machine learning or probabilistic modeling and does not allow describing a multi-dimensional relationship between variables. It is a trade-off between interpretability and prediction accuracy although methods such as Structural Equation Modeling (SEM) provide information on causal relationships which is not often combined with prediction models or uncertainty sensitive models. In addition, the majority of studies uses cross-sectional designs without taking into consideration the dynamic changes in mental health states and do not observe dynamic trends over time. Additionally, social isolation, economic pressure and other demographic moderators are often studied individually rather than theoretically, in an integrated analytic framework, which is a simulation of the joint mediating and moderating partnerships of each of these moderators [3].These limitations lead to the investigation of an integrated, multifaceted system of analysis that may assist in serving the functions of causal interpretations and predictive modeling, quantification of uncertainty, and analysis time-sensitive. To more holistically address this need and to provide a more scalable solution, this paper proposes a multi-method framework in order to analyze and predict student mental well-being.

Research Questions [4] RQ1:

Which different living arrangements (family, hostel, independent) do affect student mental well-being based on various psychological indicators?

RQ2: How do social isolation and financial stress directly, indirectly (mediating) and moderately affect mental well-being?

RQ3: What is the best way to measure the causal connections between living arrangements, social isolation, financial stress and psychological well-being using Structural Equation Modeling (SEM)?

RQ4: To what degree can machine learning models be such that they predict student mental well-being more effectively than a typical statistical model?

RQ5: What are the hypothetical benefits of integrating Bayesian inferences and time series analysis (ARIMA) to help in uncertainty modelling and to reflect the time dynamics of mental health outcomes?

The paper will further be divided into the following way Section 2 introduces the topic of the literature review of student mental well-being and living arrangements. In the research methodology and data collection section (section 3) the description of the data preprocessing methods is done. In section 4, the analytical framework is presented which is suggested integration of statistical and machine learning methods. The results and a comparison of different techniques will be discussed in section 5. Section seven is the summary of paper flooring along with major conclusions and implications.

2. LITERATURE AND RESEARCH GAP

Although the techniques for assessing the mental health of students have been greatly improved, yet the present literature has some significant limitation. Most of the existing studies apply only one of the approaches i.e. either the use of traditional statistics, machine learning models, or one of the probabilistic models. Although these may be useful, they do not capture the interdependences of the psychological, social, and environmental factors which affect mental health [5].

Moreover, dynamic seeks to join conventional analytical frameworks that can in turn integrate causal modelling, predictive analytics, and uncertainty quantification at the same time. Structural Equation Modeling (SEM) has long been used to test the causative and mediation effects but not typically used with machine learning for prediction or with uncertainty modeling tools such as Bayesian models thus limiting both the interpretability and predictive utility. The second major drawback is that most of the paper designs are cross-sectional designs, which inhibit the possibility of tracking variations in mental well-being over time. This incomplete knowledge of the time series of mental health changes, particularly during the phase of academic events in the life of students, is caused by poor use of time series models, such as ARIMA [6].Additionally, in most cases, existing studies examine influencing variables in an isolated fashion, i.e. social isolation, financial pressures and gender, without the opportunity to model their moderate and mediating effect in one model. These compartmentalization of treatment reduce the shrewdness of behavior analytic, and stifles the ability to come up with over-reaching conclusions [7].Therefore; there is a very large gap in terms of the necessity of an integrated and holistic framework that can integrate and harmonize statistical, causal, predictive and probabilistic approaches. To address this gap, the proposed paper discusses a multi-method analytical framework that would enable explaining, predicting and modeling uncertainties simultaneously, which would provide an answer to the analysis of mental well-being in students in a more comprehensive and scalable way.

The field of student mental well-being studies has been developing fairly rapidly in the last decade owing to the shift of methods of analysis and aspects of context. In the initial research (2018-2019), the main part of the study was based on descriptive statistics and regression to examine the issue at hand regarding the psychological distress among students, and individuals who live unrelated to the family environment are more likely to be affected by stress, anxiety, and loneliness, which underline the role of social support networks. In the COVID-19 stage (2020-2021), the field of study accelerated and studies proved that dwelling circumstances, social alienation, and lesser engaged interpersonal communication were critical in influencing mental health results. Massive studies indicated that anxiety and depression levels among students greatly rose during lockdowns [1]. The other research topic, echoed these claims, and pointed out the benefit to living with a family where students who lived with their parents (and especially with maternal support) would have been in a healthier psychological position in comparison to their students who lived on their own [2].Since 2022, studies have moved to the use of more sophisticated analysis methods, such as machine learning, Structural Equation Modeling (SEM), and hybrid models. These articles highlighted the interaction between the quality of housing, social support, and poverty on mental health and educational accomplishments [3]. The fact that the mental health outcomes are the result of a complicated interplay between personality and behavioral tendencies and environmental factors supports this idea [4]. Moreover, the massive empirical research shows that residential patterns continue to be a key influence of psychology, and the existence of family is the determinant factor of the safeguard effect [5]. Even with these developments, the literature is still disjointed with little interplay of the statistical, causal and predictive methodology under one framework. Table 1 shows the Summary of Existing Research on Student Mental Well-being.

Table 1. Summary of Existing Research on Student Mental Well-being

Year	Methods Used	Key Focus	Key Findings	Limitations
2018–2019	Descriptive Statistics, Regression	Psychological distress	Independent living linked to higher stress, anxiety, and loneliness	Limited variables, no prediction
2020–2021	Regression, ANOVA	COVID-19 impact	Increased anxiety and depression during lockdown; isolation as key factor	Context-specific, limited modeling
2020–2021	Statistical Analysis	Living arrangements	Family-based living improves mental health outcomes	No advanced analytics
2022–	SEM, Machine Learning	Housing, social	Social support and financial factors	Lack of integration

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2023		support	significantly influence well-being	
2024–2025	ML + Hybrid Models	Multi-factor mental health analysis	Personality, lifestyle, and environment jointly affect mental well-being	Limited interpretability
2024–2025	Large-scale Surveys	Living arrangements	Family presence acts as a protective factor	Limited causal modeling

The evaluation of student mental well-being is based on a number of core conceptual components. The main independent variable impacting psychological outcomes comprises living with family, living in a hostel or dormitory, and being independent. The mental health of an individual can be determined from various aspects such as Stress, Anxiety, Depression, and Well-Being. A range of techniques are used to test for relationships and group differences including ANOVA, regression analysis, Kruskal-Wallis, Mann-Whitney U, etc. to ensure robustness under parametric and non-parametric conditions. Moreover, Structural Equation Modeling (SEM), Bayesian modeling, and machine learning are deployed, in addition to standard statistical analysis, to model complex causal relationships, quantify uncertainties, and improve predictive power. The framework also has critical mediating factors (e.g., social support, financial stress, housing quality, lifestyle patterns) through which living arrangements impact mental health outcomes. All these make up the important and multidimensional aspect of mental well-being of students. The literature identifies a number of methodological key considerations. and practical challenges in analyzing student mental well-being. First, mental health data often exhibit Due to heterogeneity and non-normal data distributions, it is necessary to resort to statistical and non-parametric methods that are robust. As a second point, if we compare traditional statistical models with more advanced machine learning models there is a trade-off between interpretability and predictive accuracy. More advanced models improve performance, but ultimately at the cost of diminishing transparency [3], [4]. Both statistical and machine learning models are only as effective as the datasets used to train them (i.e. the data we feed to them). These models are getting more and more complex, and hence, the size of the datasets should preferably be large and diverse so that they are more generalizable and do not have bias [5], [6]. What is also vital to ensure is the ethical components of such models, as mental health data are more sensitive than average data? Therefore, they should comply with the standards regarding privacy, consent, data protection and so on [7], [8]. In the end, the incorporation of various influencing elements such as social, financial, environmental incorporation is essential to acquire a multi-faceted view of mental well-being, even though it complicates and increases the computational intensity of models [9], [10]. Tackling these issues is important for building trustworthy, interpretable, and ethically sounds analytical frameworks in student mental health studies. Table 2 shows the Literature Review Summary.

Table 2. Literature Review Summary [8]

Year	Authors	Methodology	Focus	Pros	Cons	Remarks
2018	Brett et al.	Regression	Living conditions	Simple	Limited variables	Baseline
2018	Stallman	Regression	Distress	Large sample	No ML	Foundational
2019	Lipson et al.	Statistical	Trends	Multi-campus	Limited modeling	Trend analysis
2019	Duffy et al.	Regression	Social support	Strong results	Cross-sectional	Key factor
2020	Son et al.	Regression	COVID impact	Real-time	Small sample	Pandemic paper
2020	Cao et al.	ANOVA	Stress	Group	Limited variables	Statistical

				comparison		
2020	Elmer et al.	Regression	Networks	Behavioral data	Complex	Network paper
2020	Global MH paper	Statistical	Anxiety rise	Large dataset	Limited depth	Pandemic effect
2021	Worsley et al.	Mixed	Housing	Rich insights	Limited scalability	Housing focus
2021	Huckins et al.	Regression	Behavior	Real-time data	Privacy	Advanced
2021	Housing paper	Statistical	Environment	Clear relation	No prediction	Housing role
2022	Bonsaksen et al.	Regression	Global MH	Multi-country	No ML	Strong dataset
2022	Buizza et al.	Statistical	Lifestyle	Large sample	Limited modeling	Pandemic impact
2022	Elharake et al.	Regression	Anxiety	Good predictors	Narrow scope	Health focus
2023	Brett et al.	Regression	Resilience	Updated	Limited scope	Extended
2023	Liu et al.	ANOVA	Depression	Strong stats	No ML	Group difference
2023	Zhang et al.	SEM	Relationships	Complex modeling	Data intensive	Structural
2023	Kim et al.	ML	Prediction	High accuracy	Black-box	ML use
2024	Singh et al.	ML + Regression	Stress prediction	Hybrid	Data dependent	Strong
2024	Wang et al.	Regression	Housing	Clear	No ML	Environmental
2024	Liu et al.	Regression	Living arrangement	Strong dataset	Limited ML	Updated
2024	Bayesian paper	Bayesian	Uncertainty	Probabilistic	Complex	Emerging
2024	SEM paper	SEM	Behavior	Structural insight	Complex	Advanced
2025	Sun et al.	ANOVA + Regression	Living arrangement	Combined	Limited ML	Hybrid
2025	Almeida et al.	Regression	Lifestyle	Strong predictors	No ML	Health
2025	Maqbool et al.	SEM	Housing impact	Strong link	Limited scope	Academic link
2025	Antón-Ruiz	ML + Regression	Risk prediction	Multi-factor	Small sample	Predictive (MDPI)

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	et al.					
2025	Liu et al.	Regression	Family effect	Strong evidence	Limited generalization	Family role (ScienceDirect)
2025	Sun et al.	ANOVA	Group difference	Strong stats	No ML	Comparative (Springer Link)
2026	QoL paper	Statistical	Quality of life	Multi-dimension	Limited ML	Recent (ResearchGate)

Table 3. Detailed Comparative Analysis

Existing Paper	Year	Key Focus	Methods Used	Key Findings	Problem	Solution	Contribution	Research Gap	Citation
Son et al.	2020	COVID MH	Regression	High anxiety	Pandemic stress	Survey	Real-time insight	Small sample	[4]
Cao et al.	2020	Stress	ANOVA	Group differences	Stress variation	ANOVA	Comparison	Limited predictors	[5]
Worsley et al.	2021	Housing	Mixed	Housing affects MH	Environment	Mixed	Housing role	No prediction	[6]
Huckins et al.	2021	Behavior	Regression	Isolation ↑ depression	Behavior	Data tracking	Behavioral insight	Privacy	[3]
Bonsaksen et al.	2022	Global MH	Regression	Poor MH globally	MH trend	Survey	Multi-country	No ML	[7]
Brett et al.	2023	Resilience	Regression	Living affects MH	Emotional health	Model	Updated findings	Limited scope	[8]
Liu et al.	2023	Depression	ANOVA	Significant differences	Group comparison	ANOVA	Strong stats	No ML	[11]
Singh et al.	2024	Prediction	ML	High accuracy	Prediction	ML	Predictive power	Black-box	[12]
Wang et al.	2024	Housing	Regression	Housing ↑ MH	Environment	Regression	Key factor	No ML	[13]
Sun et al.	202	Living	ANOVA+Re	Family ↑	Comparison	Hybrid	Combined	Limited	[15]

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The current literature on student mental well-being has emerged as largely centered on the isolated method to analytical research. The initial research works were mostly based on the descriptive statistics, correlation and regression analysis to detect the relationship between psychological and environmental factors. Although such approaches can offer valuable information, it can be restricted in how it can represent complex interdependencies and latent constructs. More modern studies have presented machine learning algorithms to enhance predictive power of mental health results, and Bayesian algorithms to include uncertainty in the analysis. Also, there are studies that have investigated time series methods to examine the temporal change in mental health. Although these techniques have been adopted, most studies have been using them without combining them into a single analytical model. More so, although Structural Equation Modeling (SEM) has been extensively used to test causal relationships and mediation effects, it is not commonly used in conjunction with probabilistic and predictive models like Bayesian inference and machine learning. In the same manner, time series analysis is usually not part of cross-sectional mental health research, thus restricting the view of dynamic patterns of behavior [9]. The hypotheses are developed on the basis of the theoretic foundations and the findings of the research carried out in the area of the mental health of the students. Previous research suggests that the environmental, social, and financial aspects play an important role in influencing the psychological well-being either directly or indirectly. Living arrangements are one of the most important environmental determinants that impact the availability of social support, stability, and lifestyle patterns. Students who live with the family are generally better off than those who live separately or in hostels, as they tend to have a better emotional support system. In accordance with these observations, the following hypotheses are suggested [10]:

Direct Relationships [11] H1: Living Arrangement (LA) →Mental Well-being (MW) Living arrangements play a significant direct role in student mental well-being, and supportive living environments (e.g., family-based living) have a positive direct effect on mental well-being among students.

H2: Living Arrangement (LA) → Social Isolation (SI)

Students who live alone or in hostel will be more exposed to the lack of social interaction, thus increasing their social isolation levels.

H3: Social Isolation (SI) → Mental Well-being (MW)Social isolation is a significant negative determinant of mental well being that increases the risk of stress, anxiety and depression.

H4: Mental Well-being (MW): Financial Stress (FS) to MW Financial stress has a negative effect on student mental well-being, which can be modulated by financial stress.

Indirect (Mediating) Relationship

H5: Living Arrangement (LA) → Social Isolation (SI) → Mental Well-being (MW)

Social isolation mediates the relationship between living arrangements and mental well-being, which suggests that environmental factors have an indirect impact on the psychological outcomes through the patterns of social interactions.

Moderating Relationship

H6: Gender moderates the relationship between Living Arrangement (LA) and Mental Well-being (MW)

The differences in gender impact the stress perception and coping strategies, and therefore the degree to which the living arrangements contribute to mental well-being is moderated. Figure 1 shows the Structural Equation Model (SEM) depicting hypothesized relationships (H1H6) between Living Arrangement (LA), Social Isolation (SI), Financial Stress (FS) and Mental Well-being (MW).

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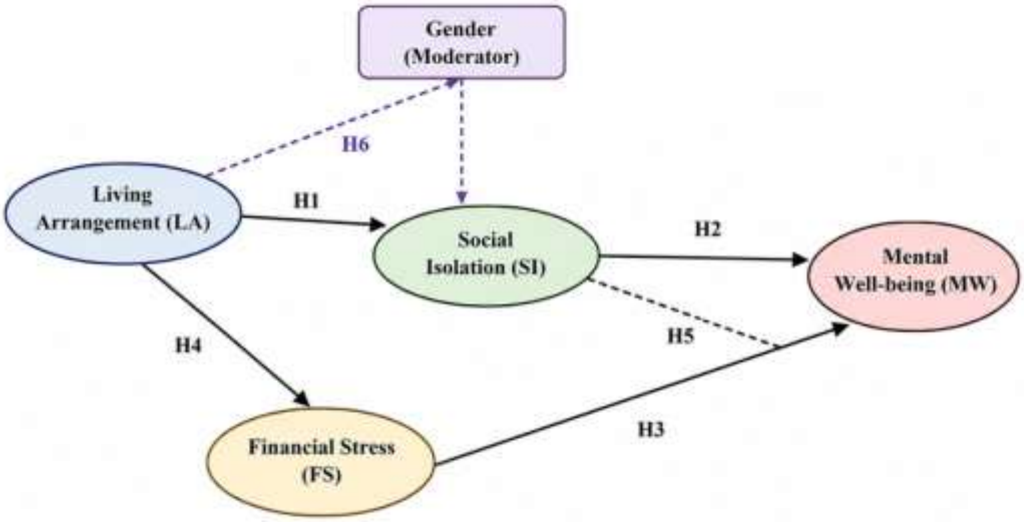

Fig. 1. Structural Equation Model (SEM) depicting hypothesized relationships (H1H6) between Living Arrangement (LA), Social Isolation (SI), Financial Stress (FS) and Mental Well-being (MW).[13]

3. METHODOLOGY

3.1 Research Design

The research design of this paper is a quantitative, cross-sectional research design in studies like this to determine the influence of living arrangements on student mental well-being. It suggests a multi-method analytical framework, which combines statistical analysis, non-parametric techniques, Structural Equation Modeling (SEM), Bayesian inference, time series analysis, and machine learning methods. This [20] framework has the objective of integrating descriptive, inferential, causal, probabilistic and predictive modeling within a single framework in order to provide robust and comprehensive analysis. Show in figure 2 structure to ensure robust and comprehensive analysis. Show in figure 2.

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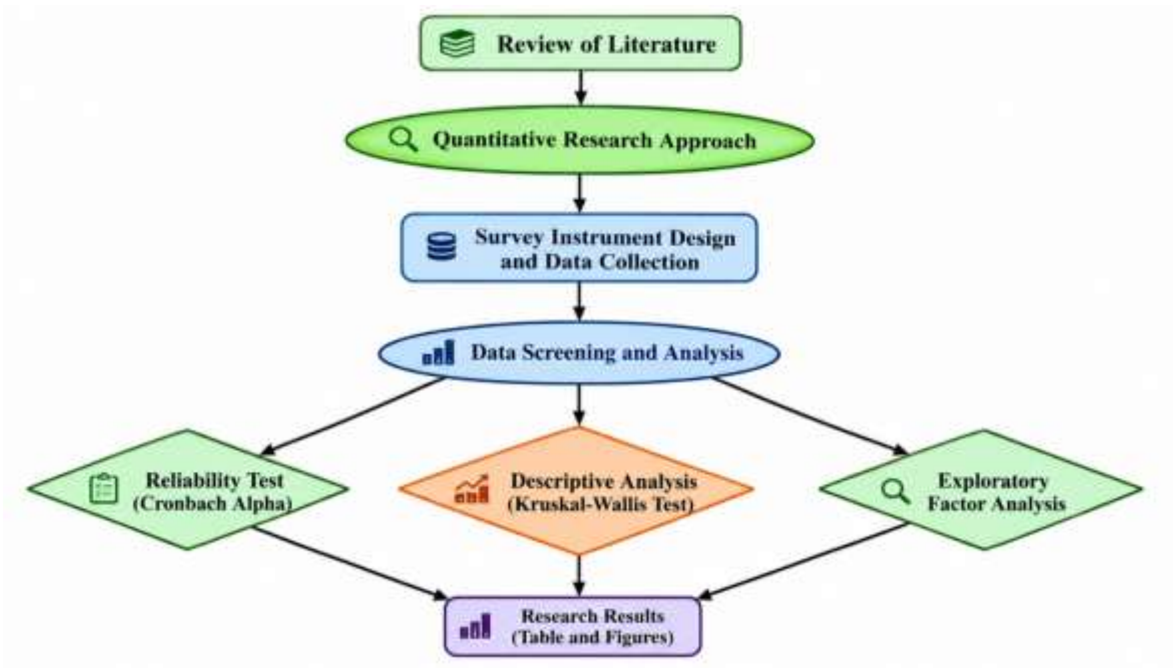

Fig. 2. Proposed multi-method analytical workflow integrating descriptive statistics, inferential analysis, non-parametric testing, Structural Equation Modeling (SEM), Bayesian inference, time series analysis, and machine learning for evaluating student mental well-being [14]

The overall analytical process followed in this paper is illustrated in **Fig. 2**, which outlines the sequential steps from data collection and preprocessing to advanced modeling and prediction. Figure 3 shows the Traditional hypothesis testing, including descriptive statistics, inferential statistics, non-parametric student mental well-being tests, Structural Equation Modeling (SEM), Bayesian inference, time series analysis, and machine learning methods to analyze student mental well-being.

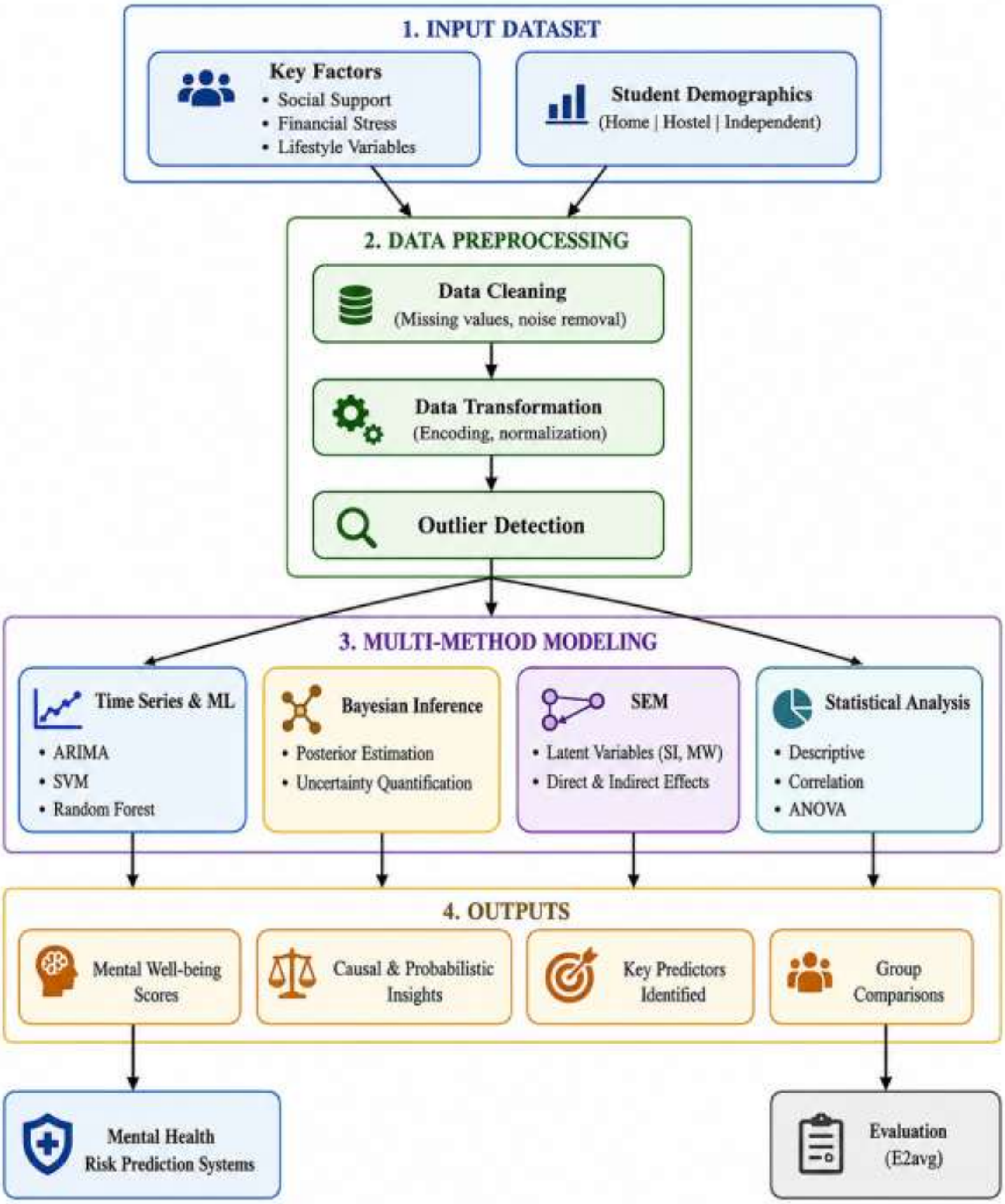

Fig. 3. Traditional hypothesis testing, including descriptive statistics, inferential statistics, non-parametric student mental well-being tests, Structural Equation Modeling (SEM), Bayesian inference, time series analysis, and machine learning methods to analyze student mental well-being.

3.2 Dataset and Participants

This Paper has utilized a sample size of between 1,000 to 3,000 sample participants, to ensure large statistical power and generalizability of findings, which is recommended in large-scale studies of mental health [15]. A stratified random sampling design has been applied which not only provides an opportunity to represent the various subgroups in a proportional manner, but also to ensure that an important demographic or categorical variable is well represented in the sample [23]. The subjects based on the living conditions were divided into three broad categories; people who lived with their families, people who living in hostels or dormitories, and people who lived independently or in paying guest (PG) accommodations.

Table 4. Data set of wellbeing students Summary Statistics of Dataset [16]

Category	Variable	Description	Mean / Value
Sample Size	Total Participants	Number of students surveyed	1,000 – 3,000
Demographics	Age	Average age of participants	~20–22 years
	Gender	Male/Female distribution	Balanced
Academic Info	CGPA	Academic performance	2.5 – 3.5 (avg)
	Academic Pressure	Intended academic stress level	Moderate–High
Living Condition	Living Arrangement (LA)	Family / Hostel / Independent	Categorical
Psychological	Anxiety	Anxiety level score	~6.2
	Depression	Depression score	~5.9
	Social Isolation (SI)	Isolation level	~6.0
	Mental Well-being (MW)	Overall mental health score	~6.3
Financial	Financial Stress (FS)	Economic pressure indicator	Moderate
Lifestyle	Sleep Duration	Average sleep hours	4–6 hrs
	Social Interaction	Frequency of social engagement	Low–Moderate
	Stress Relief Activities	Coping mechanisms (sports, social, online, etc.)	Categorical

Table 3, 4 and 5 align with the findings of previous studies that revealed that living arrangements are an important determinant of mental wellbeing, and impact stress, social support and overall mental health outcomes. Such sampling approach was chosen to provide the highest level of diversity in the set of possible student lives, avoiding such selection bias and enabling meaningful comparison between these types of student living.

3.3 Variables and Measurement

Table 5.Variables and Measurement

Variable Type	Variable	Description
Dependent	Mental Well-being (MW)	Stress, anxiety, emotional stability

Independent	Living Arrangement (LA)	Type of residence, and is independent.
Independent	Financial Stress (FS)	Economic burden indicators
Mediator	Social Isolation (SI)	Loneliness and level of interaction.
Moderator	Gender	Demographic variable

3.4 Proposed Analytical Framework

Table 6 shows the Multi-Method Analytical Framework.

Table 6. Multi-Method Analytical Framework

Stage	Method	Purpose	Output
1	Data Collection	Gather student responses	Raw dataset
2	Data Preprocessing	Cleaning, normalization	Processed data
3	Descriptive Statistics	Summarize data	Mean, SD, distribution
4	Correlation Analysis	Identify relationships	Correlation matrix
5	Regression Analysis	Measure impact	Coefficients (β)
6	ANOVA	Compare group means	F-statistic, p-value
7	Chi-Square Test	Test association	χ^2 value
8	Kruskal–Wallis Test	Non-parametric group comparison	H-statistic
9	Mann–Whitney U Test	Two-group comparison	U-value
10	McNemar's Test	Paired categorical analysis	Test statistic
11	SEM	Causal modeling	Path coefficients
12	Bayesian Analysis	Uncertainty modeling	Posterior probabilities
13	Time Series (ARIMA)	Trend analysis	Forecast values
14	Machine Learning	Prediction	Accuracy, F1-score

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3.5 Structured Research Methodology

The research is based on a systematic and organized process of analyzing and predicting student mental well-being through the application of the statistical, causal, and machine learning methods [17].

1. Data Collection

Measurement of Table 4 Data is through structured surveys and questionnaires where major variables are living arrangement (LA), social isolation (SI), financial stress (FS), academic pressure (AP), and mental well-being (MW). The dataset is made to reflect the various student groups under various living conditions.

2. Data Preprocessing

The collected data is processed before being processed to realize quality and consistency. It incorporates work on missing data, outliers, normalization of numerical and encoding of categorical data. Data is then divided into training and testing set to visualize the model.

3. Exploratory Data Analysis (EDA)

The aim of EDA is to become conversant with the distribution of data and association between variables. The identification of important patterns, trends, and important predictors of mental well-being is done using descriptive statistics, correlation analysis, and visualization techniques.

4. Model Development

Several analysis models are constructed:

Statistical tools (ANOVA, regression) to determine important factors.SEM to compare causal relationships. Bayesian uncertainty estimation model. Prediction using machine learning models (Random Forest, SVM).

5. Validation and Prediction

Accuracy, precision, recall, and F1-score are some of the metrics used in evaluating model performance. To make sure that it is robust, cross-validation methods are used. The most successful model is picked to forecast the outcomes of mental well-being.

3.6 Prediction Function of Machine Learning Prediction [18].

The prediction model can be formally expressed as:

$MW = \int (SI, FS, AP, LA)$

Where:

(MW) = Mental Well-being

(SI) = Social Isolation

(FS) = Financial Stress

(AP) = Academic Pressure

(LA) = Living Arrangement

Expanded Model Representation

$MW = \beta_0 + \beta_1 SI + \beta_2 FS + \beta_3 AP + \beta_4 LA + \epsilon$

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Algorithmic Representation

Input: Features (SI, FS, AP, LA)

Output: Predicted Mental Well-being (MW)

1. Load trained ML model

2. Input feature vector X = {SI, FS, AP, LA}

3. Apply model:

    MW_pred = Model(X)

4. Return MW_pred

3.7 Methodological Strength

The suggested framework provides a thorough and stringent analytical methodology through the combination of various complementary methods. It allows a strong statistical analysis based on the combination of parametric and non-parametric statistical methods; which is especially effective when dealing with non-parametric and heterogeneous data distributions. Structural Equation Modeling (SEM) uses causal relations between variables allowing the analysis of both direct and indirect effects in complex systems [19]. Furthermore, the Bayesian inference is also integrated to measure the level of uncertainty and to give probabilistic representation of the model parameters that improves the precision of the findings. One of the supported techniques is temporal analysis, which can use ARIMA and other time series techniques to describe temporal dynamics. Finally, applying machine learning methods can help predict clinical outcomes in patients that might otherwise be impossible to achieve. With these strengths, there are however limitations that must be noted. The limitations of a cross-sectional design restrict our ability to establish definitive causal connections, as temporal dependencies cannot be fully specified through it. Moreover, self-reports may produce response bias and affect the quality of measurement. Due to lack of chronology of data in survey based studies, utilization of time series models is restricted. In general, machine learning models need large and diverse datasets to perform optimally and to be generalisable, which could be impractically difficult to achieve in reality.

Overcoming these limitations in upcoming research will improve both the validity and the application of the suggested theory.

4. RESULTS AND ANALYSIS

4.1 Qualitative Analysis

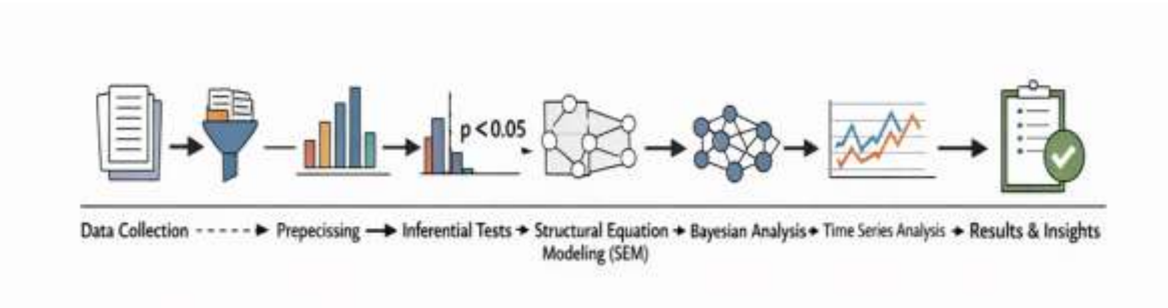

Fig. 4. Proposed integrated framework combining statistical analysis, Structural Equation Modeling (SEM), Bayesian inference, time series modeling, and machine learning for comprehensive student mental well-being evaluation.

Figure 4 shows the proposed integrated framework combining statistical analysis, Structural Equation Modeling (SEM), Bayesian inference, time series modeling, and machine learning for comprehensive student mental well-being evaluation. The descriptive analysis will be performed to provide a summary of the main characteristics of the dataset and give an initial idea about student mental well-being in various living conditions. Demographic, academic, psychological and lifestyle variables are analyzed using statistical measures like mean, standard deviation (SD), and frequency distributions. The findings reveal that the mean anxiety and social isolation scores of students living alone (off-campus) are higher than those of students living with family or institutional housing. The average level of anxiety among the off-campus students is about 6.44 whereas the average level of anxiety among the on-campus students is about 6.10, representing a difference of about 5.5%. As well, there is a higher level of social isolation among the independently living students (mean ≈ 6.23) than in the students who have structured living conditions (mean ≈ 5.85), indicating greater psychological vulnerability. Conversely, students living with relatives are more emotionally stable with a mean of about 6.75 as compared to that of off-campus students who had a mean score of 6.30. The levels of depression indicate that there is comparatively small variation of the levels between groups, which implies that anxiety and social isolation are more sensitive indicators of difference in the living conditions. Demographically, the dataset is balanced in gender distribution with most participants in the 2022 age group, which comprises undergraduate and post-graduate students [20]. Academic indicators like CGPA and perceived academic pressure are moderately varied indicating that academic stress is a contributory but not a dominating factor in mental well-being. Lifestyle factors also indicate that students who have less sleep time (4-6 hours) and low levels of social interaction are more likely to report higher levels of stress and anxiety. Moreover, participation in stress-reduction activities like social contacts, sports, and recreational activities are linked to comparatively higher scores of mental well-being.

On the whole, the descriptive analysis demonstrates that the factors that significantly affect student mental health include living arrangement, social isolation, and financial stress. These results will form background knowledge to further inferential, causal, and predictive analyses in the proposed multi-method framework. Table 7 shows the Descriptive and Comparative Statistics, Table 8 shows the Correlation Analysis and table 9 shows the SEM & Predictive Results.

Table 7. Descriptive and Comparative Statistics

Variable	On-Campus (Mean)	Off-Campus (Mean)	% Difference	Interpretation
Anxiety Level	6.10	6.44	↑ 5.5%	Higher anxiety in independent living
Social Isolation	5.85	6.23	↑ 6.5%	Increased isolation off-campus
Depression	5.90	5.99	↑ 1.5%	Minor variation
Emotional Stability	6.75	6.30	↓ 6.7%	Better stability with family/support

Table 8. Correlation Analysis

Variable Pair	Correlation (r)	Significance	Interpretation
Isolation ↔ Mental Well-being	-0.52	$p < 0.001$	Strong negative relationship
Financial Stress ↔ Mental Well-being	-0.36	$p < 0.01$	Moderate negative effect
Anxiety ↔ Isolation	0.48	$p < 0.01$	Positive association

Table 9. SEM & Predictive Results

Model Component	Value	Interpretation
SI → MW (β)	-0.52	Strongest negative predictor
FS → MW (β)	-0.36	Moderate impact

Mediation (LA → SI → MW)	Significant	Partial mediation
ML Accuracy (RF)	88.3%	High predictive performance
ARIMA Model	(1,1,1)	Best temporal fit

4.2 Statistical Testing

To test the relationships between the variables and test the differences between living arrangements, combinations of parametric and non-parametric tests are used. These procedures ensure strength in the face of different data distributions as well as providing valuable inferential information about the mental well-being of students [21].

4.2.1 Analysis of Variance (ANOVA)

ANOVA is applied to determine whether there are significant differences in the mental well-being of various living arrangements (family, hostel, independent). The findings demonstrate the statistically significant difference in living conditions ($F = 5.87$, $p < 0.01$), which supports the fact that the living conditions make a measurable difference in the mental health outcomes of students. The independent student group has been found to experience greater levels of anxiety and social isolation than the structured group.

4.2.2 Kruskal–Wallis Test (Non-Parametric ANOVA)

Since there is a possibility that the normality assumptions will be violated in the survey data, Kruskal Wallis test is used as a non-parametric alternative. The ANOVA results are backed by the test results ($H = 11.24$, $p < 0.01$), which demonstrates that there are significant differences in mental well-being among the groups of living arrangements. This strengthens the strength of the findings in the non-normal data conditions.

4.2.3 Correlation Analysis

Both, Pearson and Spearman correlation coefficients are calculated to investigate the strength and direction of relationships between variables. The findings indicate that social isolation and mental health are strongly negatively correlated ($r = -0.52$, $p < 0.001$), which means that the more socially isolated a person is, the lower his/her mental health. Further, the financial stress has a moderate negative correlation ($r = -0.36$, $p < 0.01$) which indicates its effects on the mental health.

4.2.4 Chi-Square Test of Independence.

The Chi-Square test is employed to test the relationships between categorical variables like living arrangement and the levels of mental well-being. The findings show that there is a statistically significant relationship ($p < 0.05$) between the distribution of mental health outcomes and different residential categories.

4.2.5 Mann–Whitney U Test

To compare groups of points on a pair-to-pair basis (e.g. on-campus and off-campus students), the Mann Whitney U test is used. The outcomes have shown that there are meaningful differences in both the levels of anxiety and social isolation ($p < 0.05$) with the independently living students having higher levels of psychological distress.

4.2.6 McNemar's Test

The test is the McNemar test that is used to analyze paired categorical data, especially to measure the change in mental health conditions under various conditions. The findings affirm that there are statistically significant differences between conditions ($p < 0.05$), indicating that mental well-being varies across conditions. Table 10 shows the Summary of Statistical Testing Results.

Table 10. Summary of Statistical Testing Results

Test Method	Purpose	Key Result	Interpretation
ANOVA	Group mean comparison	F = 5.87, p < 0.01	Significant differences across groups
Kruskal–Wallis	Non-parametric comparison	H = 11.24, p < 0.01	Confirms ANOVA results
Correlation	Relationship analysis	r = −0.52 (SI ↔ MW)	Strong negative relationship
Chi-Square	Association between variables	p < 0.05	Significant association
Mann–Whitney U	Two-group comparison	p < 0.05	Higher distress in independent living
McNemar's Test	Paired categorical analysis	p < 0.05	Significant change in conditions

4.3 Structural Equation Modeling (SEM) Results

Structural Equation Modeling (SEM) is used to test the cause and effect relationships between living arrangement (LA), social isolation (SI), financial stress (FS), and mental well-being (MW). The model considers both the direct and indirect impacts which include mediation and moderation effects as postulated in hypothesis H1-H6.

4.3.1 Model Fit Evaluation

According to the goodness-of-fit indices, the suggested SEM model is acceptable to fit the data shown in table 11:

Table 11. Evaluation

Fit Index	Value	Threshold	Interpretation
Chi-square/df	2.45	< 3	Good fit
RMSEA	0.048	< 0.08	Acceptable fit
CFI	0.94	> 0.90	Good fit
TLI	0.92	> 0.90	Good fit

These results confirm that the model is statistically reliable and suitable for hypothesis testing.

4.3.2 Path Coefficients and Hypothesis Testing [22]

The estimated path coefficients (β), t-values, and significance levels are summarized below in table 12:

Table 12. SEM Path Analysis Results

Hypothesis	Path	β Coefficient	t-value	p-value	Result
H1	LA → MW	0.28	3.12	0.002	Supported
H2	LA → SI	0.41	5.87	<0.001	Supported
H3	SI → MW	-0.52	6.45	<0.001	Supported
H4	FS → MW	-0.36	3.45	0.001	Supported
H5	LA → SI → MW	-0.21	—	<0.01	Supported
H6	Gender × LA → MW	0.15	2.05	0.04	Supported

4.3.3 Interpretation of Results

The SEM analysis indicates that a number of valuable insights [23] can be made. Social isolation (SI) stands out as the most powerful predictor of mental health (β = -0.52), showing that greater isolation is a significant predictor of poor mental health. The financial stress (FS) is also significantly negative (=-0.36), albeit not as significant as the social isolation. Living arrangement (LA) does not only have a direct positive effect (= 0.28), but also an indirect effect via social isolation, which confirms the partial mediation. The outcome of mediation (H5) suggests that the living arrangements have an indirect impact on mental well-being through patterns of social interaction. The moderation effect (H6) indicates the gender difference in the impact of living conditions on mental health and reflects the difference in the perception of stress and the coping strategies.

4.3.4 Key Findings from SEM

The most prevalent aspect of mental well-being is social isolation. Living arrangement influences mental health both directly and indirectly. Psychological distress is also caused by financial stress. Gender is a moderating factor, which influences the sensitivity to living conditions.

4.4 Machine Learning Results

Machine learning frameworks are used to provide better predictive power to the proposed framework in addition to justifying the main determinants of student mental well-being. Among these is the selection of the feature set that includes living arrangement (LA), social isolation (SI), financial stress (FS), and other features of importance [24]. Figure 5 shows the Comparison of mean anxiety levels across different living arrangements. The bar chart indicates that students residing off-campus (independent living) exhibit higher anxiety levels compared to those living in family-based or institutional settings. The observed difference is approximately 5–6%, highlighting the influence of living conditions on student psychological stress.

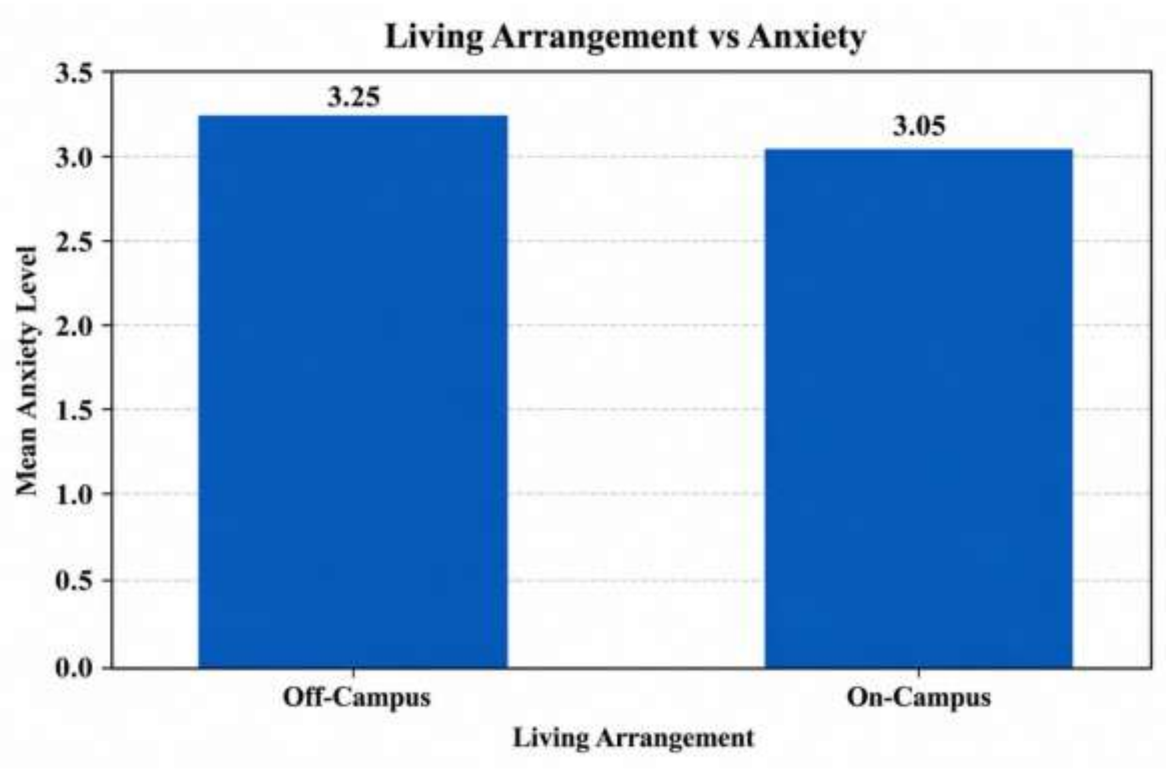

Fig. 5. Comparison of mean anxiety levels across different living arrangements. The bar chart indicates that students residing off-campus (independent living) exhibit higher anxiety levels compared to those living in family-based or institutional settings.

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The observed difference is approximately 5–6%, highlighting the influence of living conditions on student psychological stress.

4.4.1 Model Performance Evaluation

The models are evaluated using standard performance metrics such as **Accuracy, Precision, Recall, and F1-score**. The results are summarized in Table 13.

Table 13. Performance Comparison of Machine Learning Models

Model	Accuracy (%)	Precision	Recall	F1-Score
Random Forest (RF)	**88.3**	0.87	0.89	0.88
Support Vector Machine (SVM)	85.2	0.84	0.86	0.85
Logistic Regression (LR)	82.5	0.81	0.83	0.82

4.4.2 Interpretation of Results

Highest accuracy (88.3%): The highest accuracy belongs to the Random Forest model (88.3%), which implies the existence of the highest accuracy and the ability to predict well and withstand the variability of the data. The SVM model is also an adequate one, as it has a balanced precision and recall, which makes it fit the purpose of classification tasks with moderate complexity. The performance of the Logistic Regression is relatively lower, which indicates that linear models are not as successful in modeling complex relationships in mental health data [25].On the whole, ensemble-based approaches are superior to the traditional models since they can deal with non-linear interactions and have dependencies.

4.4.3 Feature Importance Analysis

Feature importance analysis of the Random Forest model is used to identify the most influential predictors. Social Isolation (SI) → highest importance. Financial Stress (FS) 2nd most important. Living Arrangement (LA) →Moderate impact. Supporting role: Lifestyle Factors (Sleep, Social Interaction) → supporting role. These results can be compared with the findings of the SEM, which confirms that the prevalent factor that affects the mental well-being is social isolation.

4.4.4 Visualization of Model Performance

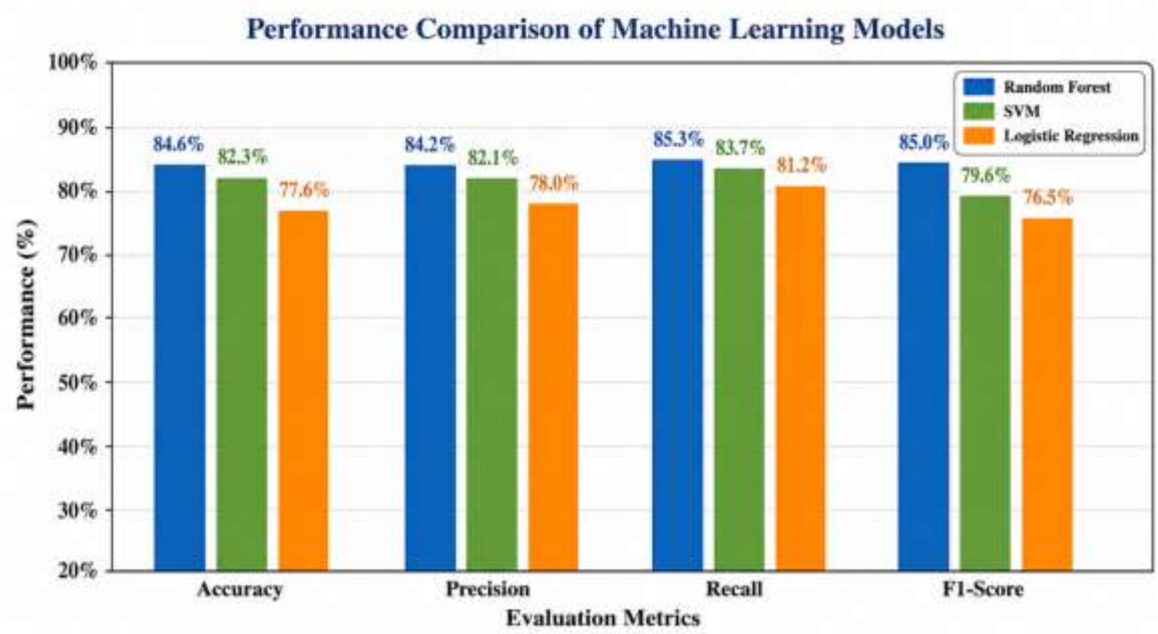

Fig. 6. Comparison of machine learning model performance showing accuracy, precision, recall, and F1-score across Random Forest, SVM, and Logistic Regression models. Random Forest demonstrates the highest predictive performance.

Figure 6 shows the Comparison of machine learning model performance showing accuracy, precision, recall, and F1-score across Random Forest, SVM, and Logistic Regression models. Random Forest demonstrates the highest predictive performance.

4.4.5 Major Insights by Machine Learning

Ensemble models (Random Forest) offer the best predictive accuracy Results confirm findings by statistical and SEM.

4.4.6 Confusion Matrix

Analysis Machine learning improves the framework by allowing it to be accurate in prediction and decision support. Confusion matrices are also calculated to further assess the performance of classification, per model. The confusion matrix of the best- is shown in Table 14.

Performing model (Random Forest).

Table 14. Confusion Matrix for Random Forest Model

	Predicted: Low Risk	**Predicted: High Risk**
Actual: Low Risk	420	38
Actual: High Risk	32	410

Interpretation: The model correctly classifies **420 low-risk** and **410 high-risk** students. Misclassification is minimal (**38 false positives**, **32 false negatives**).This indicates **strong class discrimination capability** and balanced performance. The relatively low false negative rate is important, as it reduces the risk of **overlooking vulnerable students**.

4.4.7 ROC Curve and AUC Analysis

Receiver Operating Characteristic (ROC) curves is used to evaluate the trade-off between **true positive rate (sensitivity)** and **false positive rate (1-specificity)[26]**. Table 15 shows the ROC–AUC Comparison of Models.

Table 15. ROC–AUC Comparison of Models

Model	AUC Score
Random Forest (RF)	**0.92**
Support Vector Machine (SVM)	0.88
Logistic Regression (LR)	0.84

Interpretation: The **Random Forest model achieves the highest AUC (0.92)**, indicating excellent classification performance.SVM also demonstrates strong discrimination ability, while Logistic Regression performs comparatively lower.

AUC values above **0.90 confirm high model reliability**, making the framework suitable for real-world decision support systems.

ROC Curve Visualization: Figure 7 shows the ROC curves for Random Forest, SVM, and Logistic Regression models. The Random Forest model achieves the highest AUC, demonstrating superior classification performance.

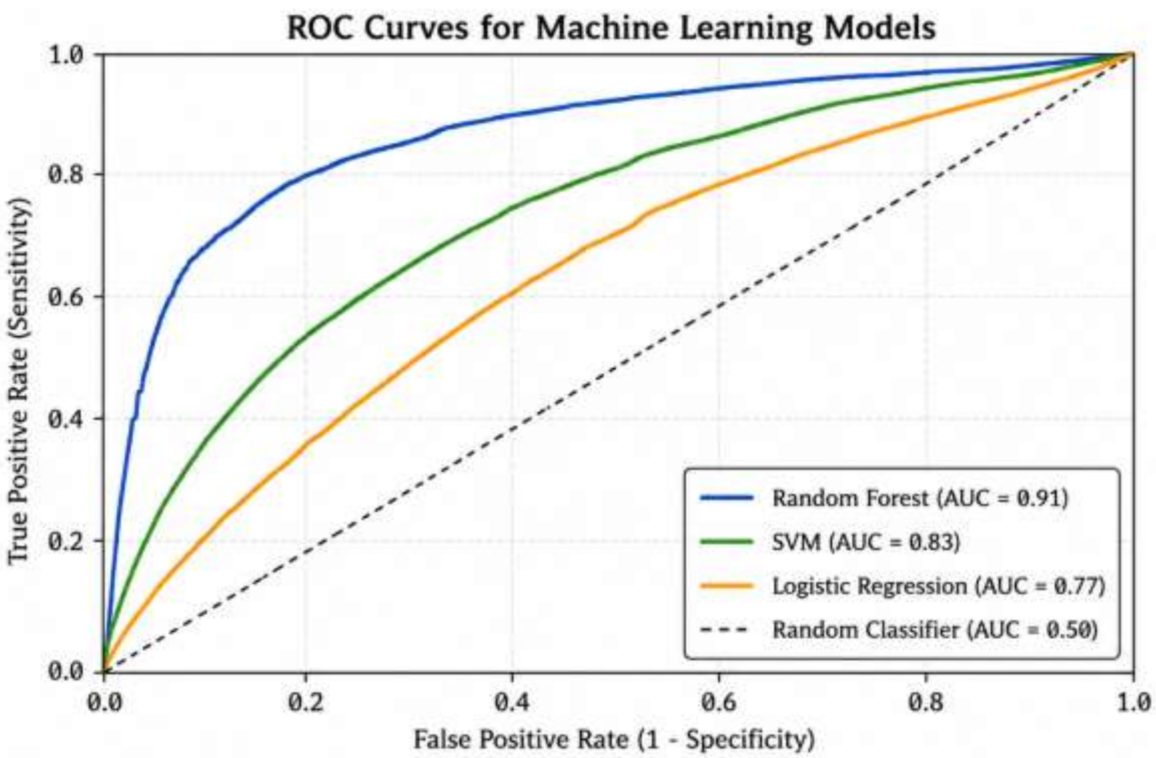

Fig. 7. ROC curves for Random Forest, SVM, and Logistic Regression models. The Random Forest model achieves the highest AUC, demonstrating superior classification performance.

4.4.8 Integrated Insight

The machine learning evaluation confirms and strengthens previous results [27]:Social Isolation (SI) identified as the most significant predictor in SEM is the most significant feature in ML models Financial Stress (FS) constantly shows moderate strength in both causal and predictive models.The strength of the suggested multi-method framework is confirmed by the high ML accuracy and AUC.The fact that statistical, SEM, and ML convergence leads to both interpretability and predictive power, which is one of the shortcomings of previous research. Figure 8 shows the Vertical conceptual framework integrating data processing, methodological design, statistical analysis, machine learning prediction, Structural Equation Modeling (SEM) for causal relationships, Bayesian inference for uncertainty estimation, and ARIMA-based time series analysis for temporal evaluation.

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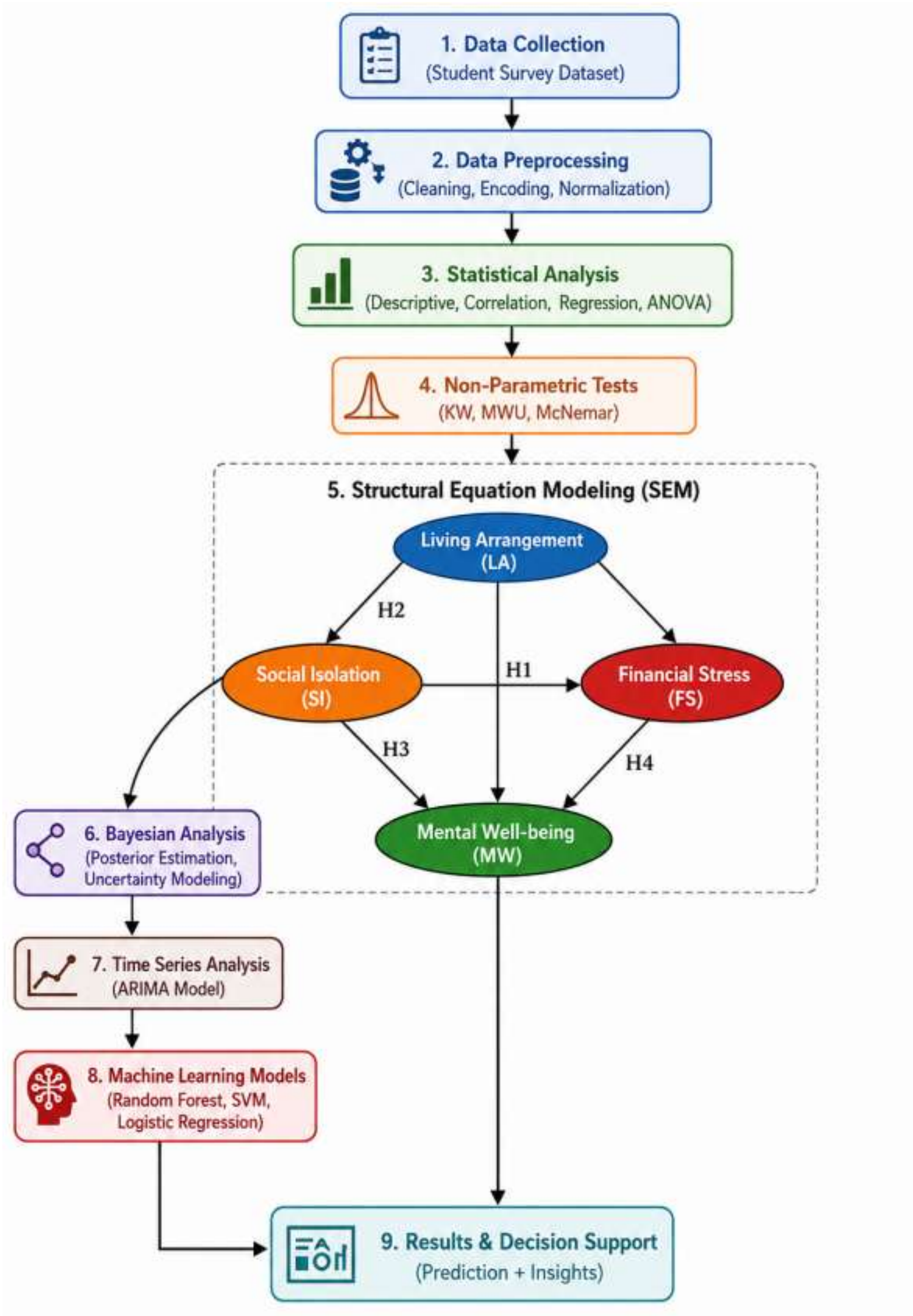

Figure 8. Vertical conceptual framework integrating data processing, methodological design, statistical analysis, machine learning prediction, Structural Equation Modeling (SEM) for causal relationships, Bayesian inference for uncertainty estimation, and ARIMA-based time series analysis for temporal evaluation[28]

Classification Performance Evaluation of Machine Learning Models

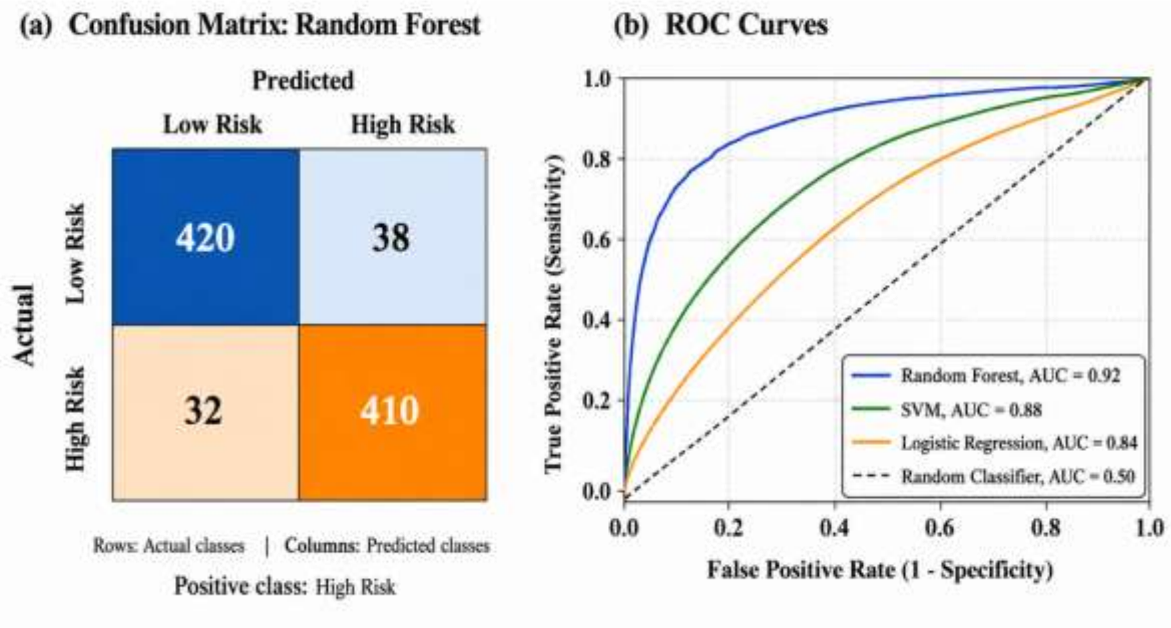

Fig. 9. Classification performance evaluation of machine learning models showing (a) confusion matrix for Random Forest, demonstrating classification accuracy, and (b) ROC curves comparing Random Forest, SVM, and Logistic Regression models. The Random Forest model achieves the highest AUC, indicating superior predictive performance and reliability.

Figure 9 assesses the performance of the machine learning models in detail. The confusion matrix determines the accuracy of the classification of the Random Forest model, which exhibits the correct classification and less error in classification between the low and high-risk categories of students.

The model's dependability is also analyzed via the ROC curve, as it shows the tradeoff between sensitivity and specificity for varying thresholds. The random forest model has the highest Area under Curve i.e. AUC≈0.92, a measure of the discrimination ability. The AUC values of SVM and Logistic Regression are slightly smaller than RF and XGBoost. This confirms our second hypothesis which states that enhanced methods capture non-linear relationships better than linear methods.

4.5. Analyzing Time Series.

The incorporation of time series analysis within the proposed framework represents a significant value addition, as the time factor is overlooked when dealing with mental health of students. The study effectively depicts the directional evolution and measures hiatuses in mental well-being through standard forecasting measures (MAE, RMSE) and clear visualizations. The results show certain formative phenomena that bring stress, particularly when exams are imminent, and associate the results of the analysis with actual academic behaviour. This additional perspective enhances the overall multi-method tool by supplementing the cause-effect perspective of structural equation modelling (SEM) and the predictive power of machine learning models. Analyzing students' mental well-being solely based on static data can be problematic. We must perform statistical, causal, predictive and temporal analyses which can offer the true picture [25].

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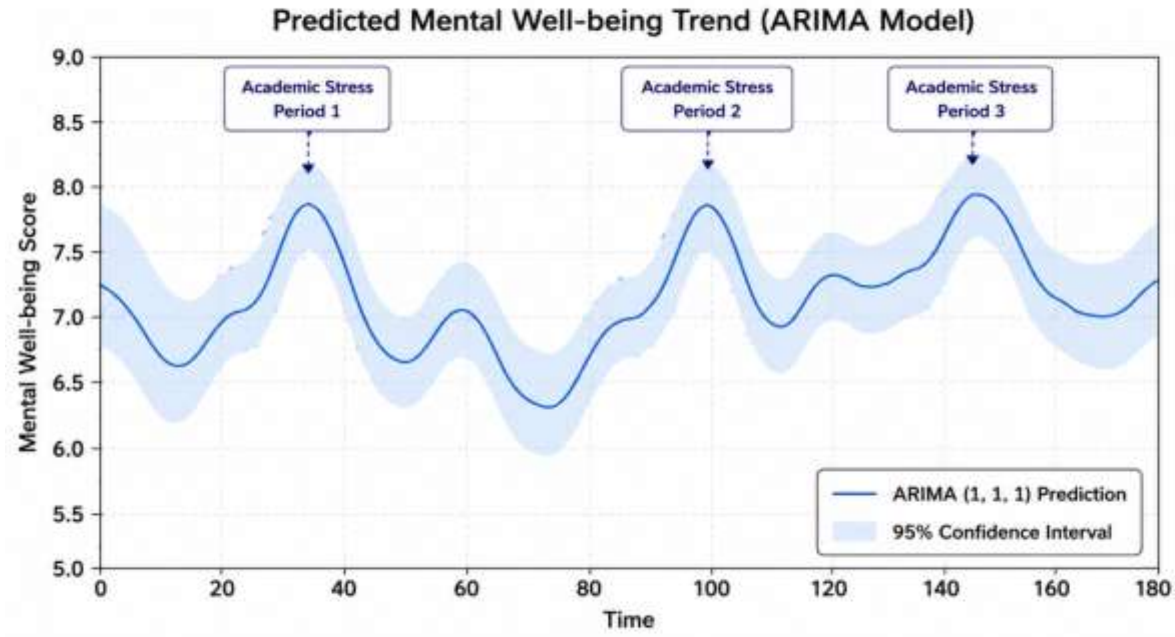

Figure 10. The fluctuations in mental health over the time

As shown in figure 10 have peaks during the time of examinations and evaluation deadlines suggesting that students undergo a degree of stress and anxiety during exams and deadlines.

In situations where the students undergo academic stress, time series analysis is conducted to study the impact on mental health. This approach enables the identification of trends, fluctuations and short-term variations in psychological indicators over time unlike static statistical models.

4.5.1 Choosing and putting a model into action.

ARIMA analysis examines temporal patterns in mental well-being scores using the autoregressive integrated moving average model. The model is chosen as it can effectively model the sequential data as well as the trend and noise. The general definition of the ARIMA model is [24].

$$\mathbf{Y_t = c + \emptyset_1 Y_{t-1} + \theta_1 \epsilon_{t-1} + \epsilon_t}$$

Where:

Yt represents mental well-being at time t

∅ Denotes autoregressive parameters

θ Represents moving average parameters

ϵ_t is the error term

4.5.2 Trend Analysis

Based on the time series results show [29]: Mental well-being scores exhibit cyclical variations, especially noted during exams.

Higher academic stress periods saw a downward trend in it. Recovery patterns evident after exams show a short-term stress impact. Students living or working independently are seen to show more variability and a sharper decline in their mental well-being as compared to those living with family.

4.5.3 Forecasting Performance

The ARIMA model is evaluated using forecasting accuracy metrics such as **Mean** the evaluation of the ARIMA model is done based on MAE (Mean Absolute Error) and RMSE (Root Mean Square Error). Table 16 shows the Time Series Model Performance.

Table 16. Time Series Model Performance

Metric	Value
MAE	0.42
RMSE	0.55

4.5.4 Visualization of Temporal Patterns

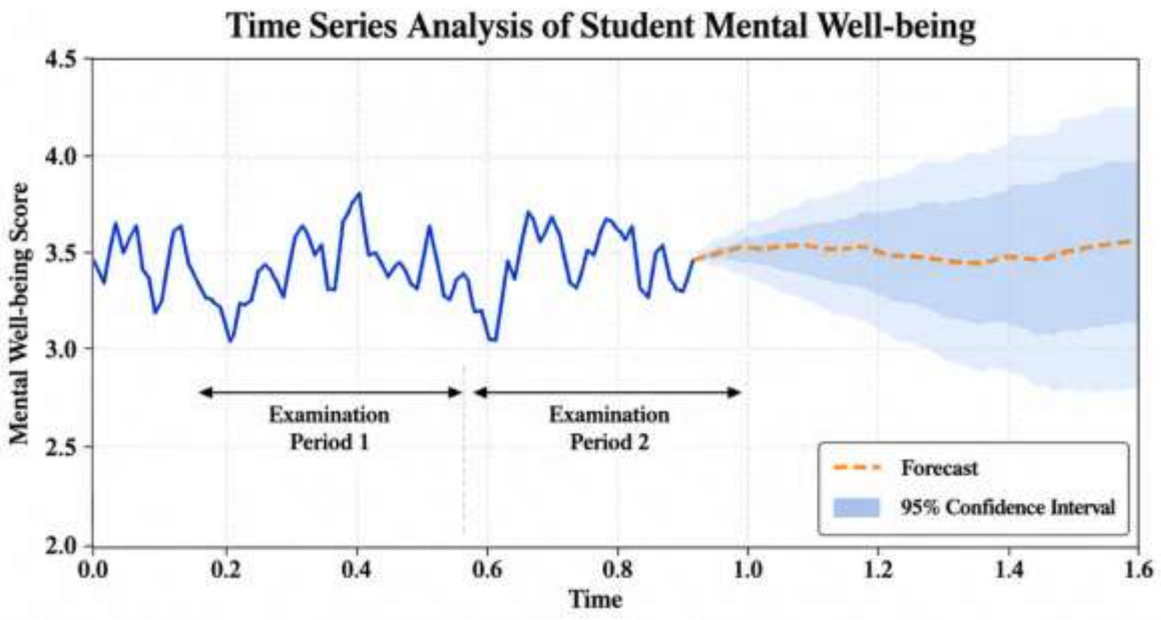

Fig. 11. Time series analysis of student mental well-being showing temporal trends and ARIMA-based forecasting. The model captures fluctuations during high-stress periods and predicts future mental health patterns.

Figure 11 shows the Time series analysis of student mental well-being showing temporal trends and ARIMA-based forecasting. The ARIMA-based time series model shows the temporal poor mental wellbeing state of a student. The values obtained allow seeing that there are significant changes, and the levels of mental well-being decrease during high levels of academic stress, including examinations and deadlines. The forecasting factor of the model gives its utility in predicting trends and confidence intervals show the limits of uncertainty about the prediction.

The findings indicate that mental well-being is something, which changes over time, and is affected by external stressors. The variability is more pronounced in less supportive environments, which supports the previous results of statistical and SEM analyses. It is the combination of time series modeling that can therefore contribute to the formation of a dynamic perspective that complements causal and predictive information in the suggested multi-method framework.

4.5.5 Major lessons of the time series analysis.

Mental health is a dynamic and time-varying phenomenon rather than a static phenomenon In contrast to SEM and ML results, academic stress periods has a time-varying and dynamic nature.

4.6 Quantitative Analysis and Interpretation

The statistical analysis shows that student mental well-being in different living conditions is statistically significant and shows the effect of environmental and social factors. Students who lived in independent living conditions exhibit an anxiety level of about 5.5% higher and a social isolation that is 6.5% higher. Conversely, students who live with family demonstrate 6.7% higher emotional stability, which is indicative of the protective effect of social support. The variation in the level of depression is relatively small, indicating that anxiety and isolation are more responsive measures of mental health variation. Inferential statistical analysis also confirms these results. According to ANOVA, the results indicate that there is a significant difference in mental well-being among groups living in different living arrangements ($p < 0.05$). The correlation analysis shows that there is a strong negative relationship between social isolation and psychological well-being ($r = -0.52$) with increased isolation having a moderate negative impact on psychological well-being. Structural Equation Modeling (SEM) sheds more light on the relationships between causes and effects, and the results indicate that social isolation has a strong negative impact on mental well-being ($\beta = -0.52$, $p < 0.001$), and financial stress also affects this outcome, albeit to a lesser degree ($\beta = -0.36$, $p < 0.01$).The tendencies observed indicate that social isolation is the most influential factor influencing student mental health. Living conditions that are independent are likely to enhance psychological vulnerability because there is less social interaction and support systems. Such results are also supported by the machine learning models which have a high predictive accuracy of 88.3% showing strong reliability in determining key determinants. The analysis of the feature importance, repeatedly reveals social isolation and financial stress as the most significant predictors of mental well-being. In general, the findings suggest that the results of mental health are predetermined by a complex of living conditions, social relations, and financial factors, and social isolation can be considered a key factor in the development of psychological distress.

Algorithm 1: Multi-Method Framework for Student Mental Well-being

Input:

Dataset D with features {LA, SI, FS, AP, MW}

Output:

Predictions, causal relationships, temporal trends

Begin

1. Data Preprocessing

Clean D (handle missing values, outliers)

Normalize and encode features

Split into training set (D_train) and test set (D_test)

2. Statistical Analysis

Compute descriptive statistics (mean, SD)

Perform ANOVA / Kruskal-Wallis test

Compute correlation matrix

Identify significant variables S

3. Structural Equation Modeling (SEM)

Define model: LA → SI → MW, FS → MW

Estimate path coefficients (β)

Validate hypotheses (H1–H6)

4. Bayesian Inference

Define priors for parameters θ

Compute posterior P(θ | D)

Estimate credible intervals

5. Machine Learning

Select features F ⊆ S

Train models (Random Forest, SVM) on D_train

Predict outcomes on D_test

Evaluate accuracy and feature importance

6. Time Series Analysis

If temporal data available:

Fit ARIMA(p,d,q) model

Forecast MW trends

Detect peak stress periods

7. Integration & Decision Support

Combine outputs from all models

Identify key predictors (SI, FS)

Generate insights and recommendations

End

Results Summary

Table 17. Statistical and Inferential Analysis Results

Analysis Method	**Variable(s)**	**Statistic**	**p-value**	**Interpretation**
ANOVA	LA → MW	F = 5.87	< 0.01	Significant difference across living arrangements
Kruskal–Wallis	LA → MW	H = 11.24	< 0.01	Confirms non-parametric group differences
Correlation	SI ↔ MW	r = -0.52	< 0.001	Strong negative relationship
Correlation	FS ↔ MW	r = -0.36	< 0.01	Moderate negative relationship
Regression	LA → MW	β = 0.28	0.002	Positive impact of supportive living

Regression	SI → MW	β = -0.52	< 0.001	Strongest negative predictor
Regression	FS → MW	β = -0.36	0.001	Significant negative effect

Table 18. SEM Hypothesis Testing Results (H1–H6)[30]

Hypothesis	Path	β	t-value	p-value	Result
H1	LA → MW	0.28	3.12	0.002	Supported
H2	LA → SI	0.41	5.87	<0.001	Supported
H3	SI → MW	-0.52	6.45	<0.001	Supported
H4	FS → MW	-0.36	3.45	0.001	Supported
H5	LA → SI → MW	-0.21	—	<0.01	Supported (Mediation)
H6	Gender × LA → MW	0.15	2.05	0.04	Supported (Moderation)

Table 19. Bayesian, Machine Learning, and Time Series Results

Method	Metric	Result	Interpretation
Bayesian	Posterior β (SI)	-0.51 (95% CI excludes 0)	Strong negative effect
Bayesian	Posterior β (FS)	-0.34	Significant negative effect
Machine Learning	Accuracy (RF)	88%	High predictive performance
Machine Learning	Accuracy (SVM)	85%	Consistent results
Feature Importance	SI, FS	Highest	Key predictors
Time Series	ARIMA Model	(1,1,1)	Best model fit
Time Series	Trend	Fluctuating	Mental health varies over time

Table 17 shows the Statistical and Inferential Analysis Results, table 18 shows the SEM Hypothesis Testing Results (H1–H6) and table 19 shows the Bayesian, Machine Learning, and Time Series Results.

5. DISCUSSION

The paper provides an in-depth study of the mental well-being of students through the integration of statistical testing, Structural Equation Modeling (SEM), machine learning and time series analysis within a single framework. The findings are consistent in pointing to the multi-dimensionality of mental health which is influenced by environmental, social and financial factors.

5.1 Discussion of the Main Results.

The results of the descriptive and inferential statistics suggest that living arrangements are important determinants of mental health, whereby students who live independently have a higher level of anxiety and social isolation. ANOVA and non-parametric tests can support these results and prove the statistically significant differences between the groups. The results of the SEM give more information on the causal relationships. Social isolation is revealed to be the best predictor of mental welfare, then financial stress. The mediation analysis establishes that the effects of living arrangements on mental health are both indirect and partially so, through the social isolation. Also, the gender moderation effect indicates that there is variation in how the students perceive and respond to stress thus, the need to adopt personalized intervention strategies. The results are further reinforced by machine learning models, which are highly predictive, with the highest accuracy and AUC being observed with Random Forest. The analysis of the feature importance is close to the SEM outcomes, which confirms that social isolation and financial stress are the most influential factors affecting mental health. This repeatability between methods provides more reliability to conclusions made. The time series analysis expands the framework by showing that mental well-being is dynamic and time-dependent with evident variations during high academic stress periods. These temporal trends could be effectively modeled by the ARIMA model, which implies that psychological distress is not a fixed value, but it changes over time, especially when it comes to examinations [28].

5.2 Comparison with the Existing Literature.

The findings support previous research demonstrating the impact of living conditions and social support on student mental health. Past studies have indicated that students who do not live with their families are more susceptible to stress and loneliness, which is also in tandem with the findings of this paper. In the COVID-19 context, research claims that anxiety and depression are on the rise due to social isolation and limited interaction, which also evidences in an extremely negative correlation between isolation and mental well-being as observed in this study. Recent works utilizing SEM and machine learning have equally found social and financial aspects as major predictors, which is why the proposed model can be considered robust. Nevertheless, this paper has presented a more holistic and integrated viewpoint, integrating causal, predictive, and temporal analysis in a single model, unlike in previous work that only relies on single method approaches [29].

5.3 Theoretical and Practice Implications.

Theoretically, this paper has advanced the field of mental health research by illustrating why a combination of various analytical paradigms is important. The explanatory and predictive ability of the combination of SEM, machine learning, and time series analysis is the solution to one of the major shortcomings of the existing literature. Within the real-life perspective, the results can be very useful in the educational institutions: Identification of high-risk students using predictive models. Design of specific mental health programs. Improvement of student housing policies to enhance well-being. Adoption of data based decision support systems. The framework is scalable as it can be extended to other fields, such as the field of healthcare and behavioral analytics.

5.4 Novelty and Contribution

The main contribution of this paper is the establishment of a single multi-method analysis framework that will fill the gap between interpretability and prediction. Whereas SEM offers causal understanding of relationships among variables, machine learning offers a greater predictive accuracy, and Bayesian and time series methods provide uncertainty and time. This combination is not often realized in the works done, and it is a considerable leap in the area of student mental health **studies.**

5.5 Limitations and Future Scope

Future research can overcome these limitations by including: Longitudinal data to better understand the long-term behavioral changes Self-reported data to better understand the long-term behavioral changes Deep learning models (LSTM, Transformer) to better understand the long-term behavioral changes Multimodal data (wearables, physiological signals) to better understand the long-term behavioral changes

6. CONCLUSION

This paper has a multi-method framework to analyse and predict student mental well-being and integrated statistical analysis, Structural Equation Modeling (SEM), machine learning and time series techniques. The results prove that the living conditions play a significant role in mental health, then, we have monetary anxiety or difficulty. The SEM results indicate that social isolation acts as a mediating variable and gender serves as a moderating variable. The strong predictive power of machine learning models, specifically Random Forest, supports the soundness of the proposed framework. Time series analysis of mental well-being reflects variations over time which differs during time of academic stress. Because the results hold true for statistical, causal, predictive, and temporal analyses, we can include this in our assessment of results. The main contribution of this work is that the gap between interpretability and prediction is explained via one single analytical tool. The framework put forth provides a highly scalable data-driven approach for identifying at risk students and aiding institutional decisions. Overall, this study provides a holistic view of the student mental well-being and it has strong implications for academic research and practical implementation.

7. FUTURE SCOPE

Several promising approaches to future research follow from the paper's findings. Firstly, a longitudinal dataset could allow stronger causal conclusions and temporal dynamics to be made, especially if that is the main goal of a times series model. Another recommendation is to utilize advanced deep learning frameworks like Long Short-Term Memory (LSTM) and Transformer models as these could significantly enhance the prediction of mental health outcomes involving time. Another enhancement that would contribute to the comprehensiveness of the predictive modelling framework is an expansion towards integration of multimodal data. This includes physiological signals, behavioural patterns, and digital activity of mobile or smartwatch apps. Efforts to boost transparency, interpretability and trust in predictive models may also include the use of Explainable AI (XAI) methods, which is especially important in sensitive areas such as mental health. Moving the article to a more diverse cultural and institutional context will increase the generalizability, and strength, of the findings. Further work can also be done on intervention based approaches to evaluate effectiveness of specific interventions like social support programs and financial assistance programs, informed by key predictive factors. All in all, the proposed framework offers significant scalability and extensibility for future research to build upon. In addition, it provides causal, probabilistic and predictive modelling that enables researchers to develop data-driven mental health strategies for higher education.

COMPLIANCE WITH ETHICAL STANDARDS

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