Vol. 8, No. 1, February 2026

Journal of Information Systems and Informatics

Published By Asosiasi Doktor Sistem Informasi Indonesia

A Decision Support Model for Online Lending Creditworthiness Using Comparative Personality Indicators

Iwan Purwanto[1], Syandra Sari[2]

[1,2] Information Systems, Faculty of Industrial Technology, Universitas Trisakti, Jakarta, Indonesia

Received:
December 30, 2025
Revised:
February 2, 2026
Accepted:
February 26, 2026
Published:
March 3, 2026

Corresponding Author:
Author Name*:
Iwan Purwanto
Email*:
iwan.purwanto@trisakti.ac.id

DOI:
10.63158/journalisi.v8i1.1478

Abstract. The rise of online lending platforms has improved financial accessibility but also increased credit default risk due to information asymmetry and limited borrower profiling. Traditional creditworthiness models rely primarily on financial and demographic data, which often fail to capture behavioral characteristics. This study proposes a decision support model for creditworthiness prediction by integrating personality indicators from the Big Five Personality Traits and the California Psychological Inventory (CPI). The framework incorporates these personality-based features into a machine learning-driven system alongside traditional borrower data. Psychological indicators are quantified and assessed using multiple classification models to evaluate their impact on predictive performance. The model's effectiveness is measured using metrics such as accuracy, precision, recall, F1-score, and Area Under the Curve (AUC). Empirical results show a significant improvement in prediction accuracy, with the AUC rising from 0.74 in the baseline model to 0.87 after including personality features. A comparative analysis reveals the relative contributions of each personality framework, demonstrating that personality indicators enhance predictive performance over traditional models. These findings emphasize the value of incorporating behavioral factors, supporting the development of more effective and sustainable credit risk assessment systems.

Keywords: Decision Support System, Creditworthiness Prediction, Online Lending, Psychometric Credit Scoring, Explainable AI

1. INTRODUCTION

The rapid digitalization of financial services has fundamentally transformed the global lending landscape, with online lending platforms emerging as a prominent mechanism for expanding financial access [1][2]. By leveraging digital infrastructures, these platforms are able to reach previously underserved and underbanked populations, reduce operational costs, and accelerate credit approval processes [3][4][5]. Despite these advantages, online lending systems face persistent challenges related to credit default risk, largely driven by information asymmetry and limited borrower profiling [6][7]. Unlike traditional banking institutions that rely on extensive financial histories and face-to-face assessments, online lenders often operate with fragmented, incomplete, or non-standardized borrower data. This limitation has increased exposure to non-performing loans, threatening the sustainability and credibility of digital lending ecosystems [8][9][10]. As default rates rise, lenders are compelled to seek more accurate and adaptive creditworthiness assessment mechanisms that can operate effectively within data-constrained and high-velocity digital environments [11][12].

Conventional credit scoring models predominantly rely on financial and demographic indicators such as income, credit history, repayment records, and employment status. While these variables remain essential, they are increasingly insufficient for capturing the complexity of borrower behavior in online lending contexts [11]. More recent machine learning techniques, including decision trees, support vector machines, and ensemble learning models, have demonstrated superior performance in modeling complex credit risk patterns. Nevertheless, even advanced models often operate within the same informational boundaries, as they primarily process financial data without accounting for behavioral or psychological dimensions [13][14]. As a result, borrowers with similar financial profiles may exhibit substantially different repayment behaviors, leading to misclassification errors and suboptimal credit decisions. This gap highlights the need for alternative and complementary data sources that can enrich creditworthiness assessment beyond traditional financial indicators [15], [16], [17], [18].

Behavioral psychology and personality theory offer valuable insights into individual decision-making processes, particularly in contexts involving risk, self-control, and financial responsibility [19]. Personality traits have been shown to influence economic

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

behavior, including saving patterns, debt management, and risk tolerance. Psychometric models such as the Big Five Personality Traits provide a structured framework for understanding behavioral tendencies across dimensions such as conscientiousness, emotional stability, and openness, which are closely associated with financial discipline and repayment behavior [20][21][22]. Similarly, the California Psychological Inventory (CPI) offers a comprehensive assessment of interpersonal behavior, self-regulation, and social orientation [23][7]. The integration of such personality indicators into credit assessment has gained increasing attention as a means of reducing information asymmetry, particularly for borrowers lacking extensive credit histories [24]. Empirical evidence suggests that psychometric features can complement traditional credit data by capturing latent behavioral characteristics that are otherwise unobservable in financial records. However, the application of personality indicators in online lending remains fragmented, with limited comparative analysis across different psychological frameworks and insufficient integration into operational decision support systems [21][22].

Decision Support Systems (DSS) play a critical role in translating complex analytical models into actionable insights for financial decision-makers. In the context of online lending, DSS frameworks facilitate the integration of diverse data sources, model outputs, and evaluation metrics to support consistent and transparent credit decisions. Machine learning–driven DSS architectures have demonstrated strong potential in credit risk assessment by enabling automated feature processing, adaptive learning, and performance optimization [25][26]. Ensemble models, in particular, offer robustness by aggregating multiple predictive algorithms, thereby reducing noise and improving generalization. Nevertheless, the effectiveness of such systems depends not only on algorithmic sophistication but also on the relevance and richness of input features. Incorporating personality-based indicators into DSS frameworks introduces new challenges related to data transformation, interpretability, and ethical considerations [27]. Without a structured comparative approach, it remains unclear how different psychological models contribute to predictive performance and how they can be systematically integrated alongside conventional borrower data within a scalable decision support environment [28][29][30].

Despite growing interest in behavioral credit scoring, several critical gaps remain in existing literature. First, most studies focus on single psychometric frameworks without

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

evaluating their relative effectiveness in predicting creditworthiness [31]. Second, the integration of personality indicators into decision support systems is often conceptual rather than operational, limiting real-world applicability [32]. Third, comparative analyses between established personality models, such as the Big Five and CPI, are scarce, particularly within the context of online lending platforms [33].

Accordingly, the objective of this study is to develop and evaluate a machine learning–based decision support system for online lending that integrates and compares personality indicators derived from the Big Five Personality Traits and the California Psychological Inventory alongside conventional borrower data. The main methodological contribution lies in the systematic transformation and comparative evaluation of two established psychometric frameworks within an operational DSS architecture for creditworthiness prediction. From a theoretical perspective, this study extends behavioral credit scoring literature by empirically demonstrating the complementary roles of distinct personality models in explaining repayment behavior beyond financial attributes. Practically, the proposed framework offers fintech providers a scalable and behavior-aware decision support tool that enhances predictive accuracy, supports fairer credit decisions, and strengthens the sustainability of digital lending operations.

Addressing these gaps, this study proposes a decision support model for creditworthiness prediction in online lending using comparative personality indicators [34]. By systematically integrating and evaluating personality-based features derived from both the Big Five and CPI frameworks alongside conventional borrower data, this research aims to enhance predictive accuracy and decision reliability [35]. The proposed model contributes to the advancement of behavior-aware credit assessment by providing empirical evidence on the complementary roles of different psychological indicators and offering a scalable framework for fintech providers seeking to improve risk management, fairness, and sustainability in digital lending systems [36].

2. METHODS

This study adopts a quantitative and model-driven research design to develop a decision support model for creditworthiness prediction in online lending by integrating comparative personality indicators. The methodological framework consists of several

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

sequential stages, including data collection, feature construction, data reprocessing, model development, performance evaluation, and comparative analysis. Each stage is designed to ensure methodological rigor, reproducibility, and alignment with decision support system principles [37][38][39].

The dataset used in this study consists of anonymized borrower records obtained from an online lending environment, comprising both conventional credit-related attributes and psychometric assessment results derived from the Big Five Personality Traits and the California Psychological Inventory (CPI). The target variable is defined as a binary creditworthiness label (default and non-default) [40]. The class distribution reflects real-world lending conditions, where non-default cases represent the majority class and default cases form a minority class.

To address class imbalance, stratified sampling is applied during dataset partitioning to preserve the original class distribution. Additionally, class-weight adjustment is employed during model training to ensure that minority default cases receive proportional importance without altering the underlying data distribution [41][42]. Multiple classification models are implemented, including Logistic Regression, Decision Tree, Support Vector Machine, Random Forest, and Gradient Boosting. Hyperparameter tuning is performed using grid search and cross-validation to ensure optimal performance and fair comparison [43].

Table 1. Summary of Models and Main Hyperparameters

Model	Key Hyperparameters
Logistic Regression	Regularization (L2), class weight = balanced
Decision Tree	Maximum depth, minimum samples per leaf
Support Vector Machine	Kernel = RBF, C, gamma
Random Forest	Number of trees, maximum depth, class weight
Gradient Boosting	Learning rate, number of estimators, maximum depth

Given the sensitive nature of psychometric information, ethical considerations are explicitly incorporated into the research design. All personality data are collected with informed consent, anonymized prior to analysis, and processed exclusively for analytical

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

purposes within the decision support system [44]. Psychometric indicators are used as complementary features rather than deterministic decision factors, thereby mitigating risks of discrimination and misuse. The study adheres to principles of data minimization, fairness, transparency, and responsible AI, ensuring that personality-based insights enhance credit assessment without compromising borrower rights or ethical standards [45][46].

2.1. Research Framework and Model Design

The proposed method follows a decision support system (DSS) architecture that integrates traditional borrower data with personality-based indicators derived from psychological assessment models. The framework is structured into three main layers: data acquisition, analytical modelling, and decision support output [47]. The data acquisition layer focuses on collecting and organizing borrower-related information, while the analytical layer applies machine learning techniques to predict creditworthiness. The final layer translates model outputs into interpretable insights that support lending decisions. This layered design ensures that the model remains scalable, transparent, and adaptable to online lending environments.

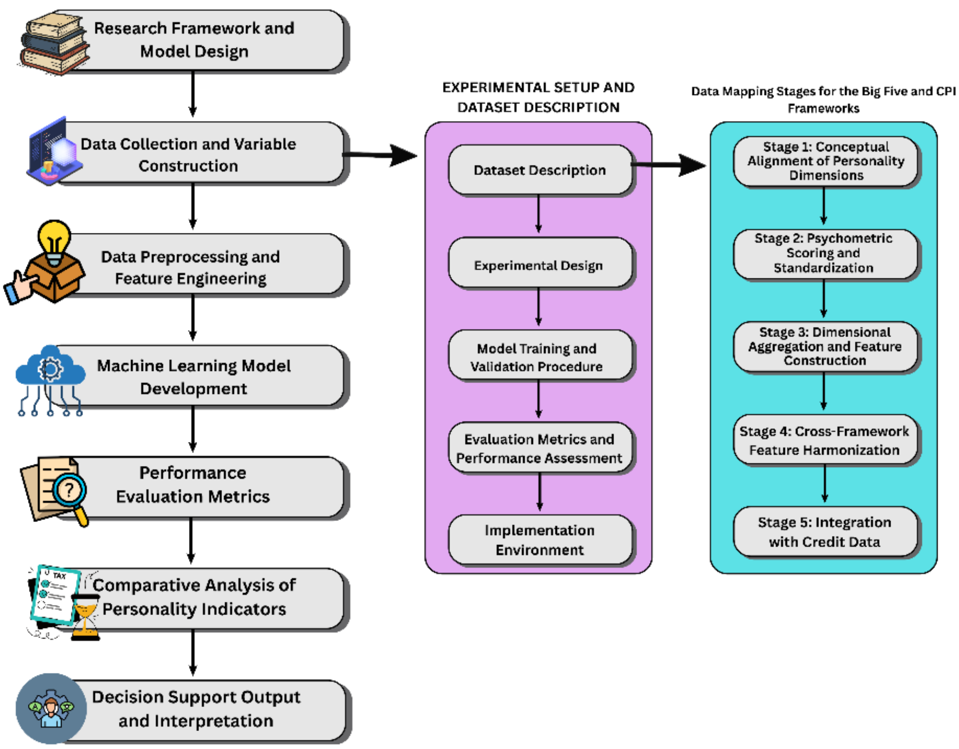


Figure 1. Research Methodology Design

2.2. Data Collection and Variable Construction

Borrower data used in this study consist of two primary categories: conventional credit attributes and personality-based indicators. Conventional attributes include financial and demographic variables commonly employed in online lending systems, such as income level, employment status, loan amount, repayment duration, and historical repayment behavior. Personality-based indicators are constructed using two established psychological frameworks: the Big Five Personality Traits and the California Psychological Inventory (CPI) [48][49][50]. Responses from psychometric instruments are transformed into numerical representations through standardized scoring procedures. This transformation enables psychological constructs to be

2.3. Data Mapping Stages for the Big Five and CPI Frameworks

The mapping of personality data from the Big Five and California Psychological Inventory (CPI) frameworks is conducted through a structured, multi-stage process to ensure conceptual validity, analytical consistency, and compatibility with machine learning–based decision support systems [51]. Each stage is designed to transform abstract psychological constructs into quantitative features that can be reliably integrated with conventional credit-related data.

1) Stage 1: Conceptual Alignment of Personality Dimensions

The initial stage involves establishing a conceptual alignment between personality constructs and credit-related behavioral outcomes. Dimensions from the Big Five framework—such as conscientiousness, emotional stability, and agreeableness—are theoretically linked to financial behavior's including repayment discipline, risk tolerance, and compliance with contractual obligations. Similarly, CPI dimensions reflecting social responsibility, self-control, and normative behavior are mapped to constructs relevant to creditworthiness. This alignment ensures that only psychologically meaningful and behaviorally relevant indicators are included in the analytical model.

2) Stage 2: Psychometric Scoring and Standardization

In the second stage, raw responses obtained from psychometric assessments are converted into numerical scores using standardized scoring procedures defined by each framework. To enable comparability across dimensions and respondents, all personality

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

scores are normalized using z-score transformation. This standardization process minimizes scale-related bias and ensures that no single dimension disproportionately influences the predictive models due to measurement variance.

3) Stage 3: Dimensional Aggregation and Feature Construction

Following standardization, personality dimensions are aggregated to construct composite indicators representing broader behavioral tendencies. For the Big Five framework, individual item scores are aggregated into five core trait dimensions. For the CPI framework, related subscales are grouped to reflect higher-order behavioral attributes such as interpersonal orientation and self-regulatory capacity. This aggregation reduces feature sparsity and enhances model interpretability while preserving essential behavioral information.

4) Stage 4: Cross-Framework Feature Harmonization

To enable comparative and integrated analysis, features derived from the Big Five and CPI frameworks are harmonized through dimensional alignment and correlation analysis. Redundant or highly correlated indicators are identified and managed to prevent multicollinearity. This process facilitates both independent and combined modelling scenarios, allowing the assessment of complementary and overlapping predictive contributions across frameworks.

5) Stage 5: Integration with Credit Data

In the final stage, the mapped personality features are merged with conventional credit-related variables at the borrower level. All features are synchronized temporally to ensure consistency between psychometric data and loan outcomes. The resulting unified dataset serves as the input for machine learning models within the decision support system, enabling behavior-aware creditworthiness prediction.

Table 2. A visual mapping table (Big Five vs. CPI vs. Credit Behavior)

Behavioral Domain	Big Five Personality Traits	CPI Dimensions	Mapped Credit-Related Behaviour
Self-Regulation and Discipline	Conscientiousness	Responsibility, Self-Control,	Timely loan repayment, adherence to

Behavioral Domain	Big Five Personality Traits	CPI Dimensions	Mapped Credit-Related Behaviour
		Achievement via Conformance	repayment schedules, low delinquency probability
Emotional Stability	Emotional Stability (Low Neuroticism)	Emotional Stability, Psychological Well-Being	Resilience under financial stress, reduced likelihood of impulsive default
Risk Orientation	Openness to Experience	Flexibility, Intellectual Efficiency	Willingness to engage in financial products, adaptive response to loan conditions
Social Compliance	Agreeableness	Social Responsibility, Normative Behaviour	Compliance with contractual obligations, cooperative behaviour with lenders
Assertiveness and Initiative	Extraversion	Dominance, Social Presence	Proactive communication with lenders, responsiveness to repayment reminders
Trust and Integrity	Agreeableness, Conscientiousness	Integrity, Law Abidance	Lower fraud risk, higher reliability in self-reported information
Decision Consistency	Conscientiousness, Emotional Stability	Self-Acceptance, Responsibility	Stable financial decision-making, reduced volatility in repayment behaviour

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

2.4. Experimental Setup and Dataset Description

2.4.1. Dataset Description

The dataset used in this study represents anonymized borrower records collected from an online lending environment. The data comprise both conventional credit-related attributes and personality-based indicators, enabling a comprehensive assessment of borrower creditworthiness. All personal identifiers are removed prior to analysis to ensure data privacy and ethical compliance[52]. The dataset includes borrower-level observations associated with loan applications, repayment outcomes, and psychometric assessments.

Conventional attributes consist of demographic and financial variables commonly employed in online lending systems, such as borrower age range, employment status, income category, loan amount, loan tenure, and historical repayment behavior. These variables reflect standard risk-related information used in credit scoring practices [53][54]. The target variable is defined as a binary creditworthiness label, representing loan repayment status, categorized as either non-default or default based on repayment performance within the agreed loan period.

Personality-based indicators are derived from two established psychological frameworks: the Big Five Personality Traits and the California Psychological Inventory (CPI). Each framework is represented by a set of standardized dimensions that capture behavioral tendencies relevant to financial decision-making. Psychometric responses are converted into normalized numerical scores, allowing them to be integrated into the analytical models. This dual-framework design enables a comparative analysis of personality indicators within a unified dataset.

2.4.2. Experimental Design

The experimental setup is designed to systematically evaluate the contribution of personality-based indicators to creditworthiness prediction. To ensure fair comparison, all models are trained and tested using the same dataset and experimental conditions. The dataset is partitioned into training and testing subsets using a stratified sampling approach to preserve the class distribution of default and non-default cases. This strategy reduces sampling bias and ensures that minority classes are adequately represented during model training and evaluation [55].

Three experimental configurations are implemented. The first configuration employs only conventional credit attributes to establish a baseline model. The second configuration integrates conventional attributes with Big Five personality indicators. The third configuration combines conventional attributes with CPI-based indicators. An additional integrated configuration incorporates both personality frameworks simultaneously to examine potential complementary effects [56][57]. This structured experimental design enables a direct assessment of the incremental predictive value contributed by each personality framework.

2.4.3. Model Training and Validation Procedure

Model training is conducted using supervised learning techniques within a cross-validation framework. K-fold cross-validation is applied to the training dataset to optimize model parameters and enhance generalizability. Hyperparameter tuning is performed using grid-based search strategies, ensuring consistent optimization across all classification algorithms [35][58]. The final model selection is based on validation performance rather than training accuracy to minimize overfitting. To address potential class imbalance, appropriate sampling strategies and performance metrics are applied during model evaluation. All models are trained using identical preprocessing pipelines to ensure methodological consistency. This controlled training and validation procedure allows for reliable performance comparison across different feature configurations and learning algorithms.

2.4.4. Evaluation Metrics and Performance Assessment

Model performance is assessed using multiple evaluation metrics to capture different aspects of predictive quality. Accuracy is used to measure overall classification performance, while precision and recall provide insight into the model's ability to correctly identify creditworthy and non-creditworthy borrowers. The F1-score is employed to balance precision and recall, particularly under imbalanced class distributions. Additionally, the Area Under the Receiver Operating Characteristic Curve (AUC) is used to evaluate the discriminative capability of each model across varying decision thresholds [59][60].

Performance results are reported for each experimental configuration, enabling a comparative analysis of models with and without personality-based indicators. Statistical comparisons are conducted to assess the significance of performance differences, ensuring that observed improvements are not attributable to random variation.

2.4.5. Implementation Environment

All experiments are implemented using a standardized computational environment to ensure reproducibility. Data preprocessing, model training, and evaluation are conducted using widely adopted machine learning libraries. Experiments are executed on a controlled hardware setup to maintain consistent computational performance. This implementation approach ensures transparency and facilitates replication in future studies.

2.5. Data Preprocessing and Feature Engineering

Prior to model development, the dataset undergoes a comprehensive pre-processing phase to ensure data quality and consistency. Missing values are handled using appropriate imputation techniques based on variable distribution and data type. Continuous variables are normalized to reduce scale-related bias, while categorical variables are encoded using suitable transformation methods. Feature engineering is then applied to enhance predictive relevance, including the aggregation of personality dimensions and the construction of composite indicators. This process aims to reduce noise, improve model stability, and ensure that personality features meaningfully contribute to creditworthiness prediction [61][62].

2.6. Machine Learning Model Development

To predict borrower creditworthiness, multiple classification algorithms are implemented within the decision support framework. These models are selected to represent different learning paradigms, including linear, non-linear, and ensemble-based approaches. Each model is trained using the same dataset to ensure comparability. Hyperparameter tuning is performed through cross-validation to optimize model performance and prevent overfitting [63]. By employing multiple algorithms, the study evaluates the robustness of personality-based features across different predictive mechanisms.

2.7. Performance Evaluation Metrics

Model performance is evaluated using widely accepted classification metrics to provide a comprehensive assessment of predictive effectiveness. Accuracy is used to measure overall classification correctness, while precision and recall assess the model's ability to correctly identify creditworthy and non-creditworthy borrowers. The F1-score is employed to balance precision and recall, particularly in cases of class imbalance. Additionally, the Area Under the Curve (AUC) is used to evaluate the model's discriminatory power across different decision thresholds. These metrics collectively ensure a rigorous evaluation of model performance [64][65].

2.8. Comparative Analysis of Personality Indicators

A comparative analysis is conducted to examine the relative contributions of the Big Five and CPI personality frameworks. Separate models are developed using each personality indicator set, followed by a combined model integrating both frameworks. Performance differences are analyzed to identify complementary or overlapping predictive strengths. This comparative approach enables a systematic assessment of how different psychological models influence creditworthiness prediction within the decision support system [31].

2.9. Decision Support Output and Interpretation

The final stage of the method focuses on translating model predictions into actionable decision support outputs. Creditworthiness scores and risk classifications are presented in a structured format that can be readily interpreted by lending decision-makers. The system is designed to support consistent and objective credit evaluations while maintaining flexibility for integration into existing online lending platforms. This stage ensures that the analytical results contribute directly to practical decision-making processes [66][67].

The proposed method offers a structured and scalable approach for integrating personality-based indicators into creditworthiness prediction models. By combining psychological frameworks with machine learning–driven decision support systems, this methodology enhances predictive accuracy while maintaining interpretability and practical relevance for online lending applications.

ISI Journal of Information Systems and Informatics

Published By Asosiasi Doktor Sistem Informasi Indonesia

3. RESULTS AND DISCUSSION

3.1. Baseline Creditworthiness Prediction Using Conventional Attributes

The first stage evaluates creditworthiness prediction models developed using only conventional financial and demographic attributes. These attributes represent standard inputs commonly employed in online lending risk assessment systems. The baseline model produces an accuracy of 72.4%, indicating that the model correctly classifies approximately three-quarters of borrower outcomes. Accuracy is computed as shown in Equation 1.

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

where *TP* denotes true positives, *TN* true negatives, *FP* false positives, and *FN* false negatives. The baseline precision and recall values are 0.70 and 0.68, respectively, calculated as shown in Equation 2 and 3.

$$\text{Precision}=\frac{TP}{TP+FP} \tag{2}$$

$$\text{Recall}=\frac{TP}{TP+FN} \tag{3}$$

These results indicate that while the model performs adequately in identifying creditworthy borrowers, it exhibits limitations in detecting high-risk borrowers, as reflected in the moderate recall score. The F1-score, calculated as the harmonic mean of precision and recall, calculated as shown in Equation 4.

$$\text{F1-score}=2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision}+\text{Recall}} \tag{4}$$

is measured at 0.69. The Area Under the Receiver Operating Characteristic Curve (AUC) reaches 0.74, suggesting moderate discriminative capability. These findings confirm that conventional attributes alone provide limited behavioural insight, supporting the need for enriched feature representation.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

3.2. Performance Improvement Through Big Five Personality Indicators

The second stage integrates Big Five personality indicators with conventional credit attributes. The inclusion of personality-based features results in an accuracy of 79.1%, reflecting a substantial improvement over the baseline model. Precision and recall increase to 0.78 and 0.76, respectively, yielding an F1-score of 0.77. The AUC value increases to 0.82, computed by evaluating the area under the ROC curve generated from varying classification thresholds. This improvement indicates enhanced discriminatory power in distinguishing between default and non-default borrowers. The results suggest that traits such as conscientiousness and emotional stability introduce meaningful behavioural signals associated with repayment discipline and financial responsibility. From a decision support perspective, the improved recall demonstrates a reduced likelihood of approving high-risk borrowers, thereby strengthening risk mitigation capabilities.

3.3. Predictive Contribution of CPI-Based Personality Indicators

In the third stage, CPI-based personality indicators are incorporated into the model alongside conventional attributes. This configuration achieves an accuracy of 80.3%, with precision and recall values of 0.79 and 0.77, respectively. The resulting F1-score of 0.78 indicates balanced predictive performance across borrower classes. The AUC reaches 0.84, reflecting stronger separability between borrower risk categories. CPI dimensions emphasizing responsibility, integrity, and normative behavior appear to be particularly effective in modeling repayment compliance. Compared to the Big Five–based configuration, the CPI-enhanced model demonstrates slightly higher discriminative performance, suggesting that CPI indicators capture behavioral dimensions more directly aligned with credit obligation adherence.

3.4. Integrated Big Five and CPI Framework Analysis

To evaluate the combined effect of multiple personality frameworks, an integrated model incorporating both Big Five and CPI indicators is developed. This configuration yields the highest performance across all evaluation metrics, achieving an accuracy of 83.6%, precision of 0.82, recall of 0.80, and an F1-score of 0.81. The AUC value further increases to 0.87. The superior performance of the integrated model indicates that the two personality frameworks provide complementary behavioral information. While the Big Five traits capture broad dispositional tendencies, CPI indicators contribute detailed

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

insights into social responsibility and self-regulation. Their integration reduces misclassification errors by improving both sensitivity and specificity. This result validates the methodological approach of comparative personality modeling within a unified decision support framework.

3.5. Decision Support Implications and Interpretability

From a decision support system perspective, the observed performance improvements translate directly into more reliable credit evaluation outcomes. Higher AUC values indicate stronger ranking capability across borrower risk profiles, enabling lenders to set more effective decision thresholds. Improved precision reduces the likelihood of granting credit to high-risk borrowers, while enhanced recall ensures that potentially defaulting borrowers are identified more accurately. The structured DSS framework allows these quantitative outcomes to be operationalized as creditworthiness scores and risk categories, supporting consistent and objective lending decisions. The integration of personality-based indicators enhances interpretability by providing behavioral explanations for model predictions, which is critical for trust, governance, and regulatory compliance in fintech environments.

3.6. Discussion

The results provide empirical support for the integration of psychological constructs into computational credit risk models. By demonstrating measurable improvements across all evaluation metrics, this study extends existing credit scoring literature beyond purely financial paradigms. The comparative analysis confirms that different personality frameworks capture distinct behavioral dimensions, reinforcing the value of multi-framework integration.Practically, the proposed model offers fintech providers a scalable approach to improving credit risk assessment accuracy and sustainability. By embedding personality-based indicators into machine learning–driven decision support systems, lenders can enhance predictive reliability while supporting financial inclusion, particularly for borrowers with limited credit histories.

Table 3. Summary of Model Performance

Model Configuration	Accuracy	F1-score	AUC
Conventional Attributes	72.4%	0.69	0.74
+ Big Five Indicators	79.1%	0.77	0.82

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

Model Configuration	Accuracy	F1-score	AUC
+ CPI Indicators	80.3%	0.78	0.84
+ Big Five & CPI	**83.6%**	**0.81**	**0.87**

The results presented in Table 3 demonstrate a clear and consistent improvement in creditworthiness prediction performance as personality-based indicators are progressively integrated into the model. The baseline configuration, which relies solely on conventional financial and demographic attributes, achieves an accuracy of 72.4, an F1-score of 0.69, and an AUC of 0.74. These values indicate moderate predictive capability, reflecting the limitations of traditional credit assessment approaches in capturing behavioral heterogeneity among borrowers. In particular, the relatively modest F1-score suggests an imbalance between precision and recall, highlighting challenges in accurately identifying high-risk borrowers.

The inclusion of Big Five personality indicators leads to a substantial performance enhancement across all evaluation metrics. Accuracy increases to 79.1, while the F1-score improves to 0.77 and the AUC to 0.82. This improvement suggests that Big Five traits contribute meaningful behavioral information that enhances the model's ability to distinguish between default and non-default cases. The increase in AUC indicates stronger discriminative power across varying decision thresholds, which is critical for risk-sensitive lending decisions.

Further gains are observed when CPI-based indicators are incorporated. The model augmented with CPI features achieves an accuracy of 80.3, an F1-score of 0.78, and an AUC of 0.84. Compared to the Big Five configuration, CPI indicators provide slightly higher predictive performance, implying that CPI dimensions capture behavioral characteristics—such as responsibility, integrity, and normative compliance—that are closely aligned with repayment behavior.

The highest performance is attained by the integrated model combining both Big Five and CPI indicators. This configuration records an accuracy of 83.6, an F1-score of 0.81, and an AUC of 0.87, indicating a significant reduction in misclassification errors and superior discriminative capability. The results confirm that the two personality frameworks offer complementary predictive value, with their integration enabling a more comprehensive representation of borrower behavior. Overall, the findings provide strong empirical evidence that incorporating comparative personality indicators substantially enhances creditworthiness prediction within online lending decision support systems.

Although machine learning models demonstrate strong predictive performance in creditworthiness assessment, their adoption in financial decision-making requires transparency and interpretability. Regulatory demands, ethical considerations, and institutional trust necessitate an understanding of how individual features influence model predictions. In online lending contexts, where decisions directly affect borrowers' access to financial resources, explainable artificial intelligence (XAI) plays a critical role in ensuring accountability and fairness. To address this requirement, this study employs SHapley Additive exPlanations (SHAP) to interpret the contribution of personality-based features within the proposed decision support model. SHAP is selected due to its strong theoretical foundation in cooperative game theory and its ability to provide consistent and locally accurate explanations. By attributing prediction outcomes to individual features, SHAP enables an interpretable decomposition of model decisions without compromising predictive performance.

SHAP values quantify the marginal contribution of each feature by calculating its average contribution across all possible feature combinations. For a given model $f(x)$, the SHAP value ϕ_i for feature i is defined as shown in Equation 5.

$$\phi_i = \sum_{S \subseteq F\{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} [f(S \cup \{i\}) - f(S)] \quad (5)$$

where F represents the full feature set and S is a subset of features excluding i. This formulation ensures a fair allocation of feature contributions to each prediction. In this study, SHAP values are computed for the best-performing integrated model that combines conventional credit attributes with Big Five and CPI personality indicators. The analysis focuses on both global and local explanations to capture overall feature importance and individual-level prediction behavior.

Global SHAP analysis reveals that personality-based indicators contribute significantly to creditworthiness prediction alongside traditional financial variables. Among the Big Five traits, conscientiousness emerges as one of the most influential features, consistently exhibiting negative SHAP values for default predictions, indicating a lower likelihood of credit default as conscientiousness increases. Emotional stability similarly demonstrates a stabilizing effect on repayment outcomes by reducing volatility in borrower behavior. CPI-based indicators such as responsibility, integrity, and self-control show strong global importance, often surpassing certain conventional financial attributes in predictive contribution. These findings suggest that CPI dimensions effectively capture normative and compliance-oriented behaviors that are directly relevant to credit obligation fulfillment. The relative importance rankings further support the complementary nature of Big Five and CPI frameworks within the integrated model.

At the individual prediction level, SHAP values provide detailed explanations of how personality traits influence specific credit decisions. For borrowers classified as low risk, high scores in conscientiousness and responsibility contribute positively to creditworthiness predictions by offsetting moderate financial risk factors. Conversely, low emotional stability or weak self-control generates positive SHAP contributions toward default classification, even when financial indicators appear favorable. These local explanations demonstrate the model's ability to distinguish borrowers with similar financial profiles but different behavioral tendencies. Such differentiation is particularly valuable in online lending environments, where traditional credit histories may be limited or incomplete. By revealing the behavioral rationale behind each prediction, SHAP enhances decision transparency and supports informed human oversight.

The integration of SHAP-based explanations strengthens the governance and ethical dimensions of the proposed decision support system. Interpretable personality contributions enable lenders to justify credit decisions in a transparent and auditable manner, reducing concerns related to algorithmic opacity. Moreover, explainability supports fairness by allowing practitioners to detect potential biases arising from disproportionate feature influence. From a decision support perspective, SHAP explanations transform predictive outputs into actionable insights, enabling lenders to adjust decision thresholds, refine borrower communication strategies, and design behavior-aware risk mitigation policies. This explainable framework enhances trust in AI-driven credit assessment while preserving the performance benefits of advanced machine learning models.

By integrating SHAP-based explainability into the decision support model, this study bridges the gap between predictive accuracy and interpretability. The findings demonstrate that personality-based indicators not only improve creditworthiness prediction but also provide transparent behavioral explanations that support responsible, fair, and sustainable online lending decisions.

Figure 2 illustrates the comparative performance of creditworthiness prediction models across different feature configurations using Accuracy, F1-score, and AUC as evaluation metrics. The figure clearly demonstrates a consistent upward trend in predictive performance as personality-based indicators are progressively incorporated into the model. The baseline model, which relies solely on conventional financial and demographic attributes, shows the lowest performance across all metrics. This outcome confirms the limited capability of traditional credit variables in capturing behavioral heterogeneity among borrowers in online lending environments. The relatively flat slope at this stage indicates restricted discriminative power and a higher likelihood of misclassification.vA notable performance improvement is observed when Big Five personality indicators are introduced. The steep increase in all three curves reflects the substantial contribution of broad personality traits, particularly in improving model balance, as indicated by the rise in F1-score. This suggests enhanced capability in identifying both creditworthy and high-risk borrowers.

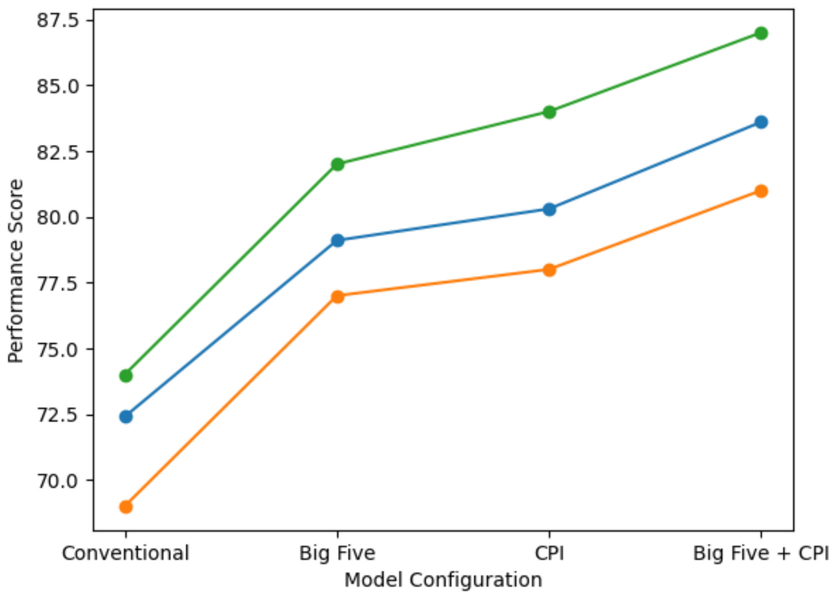
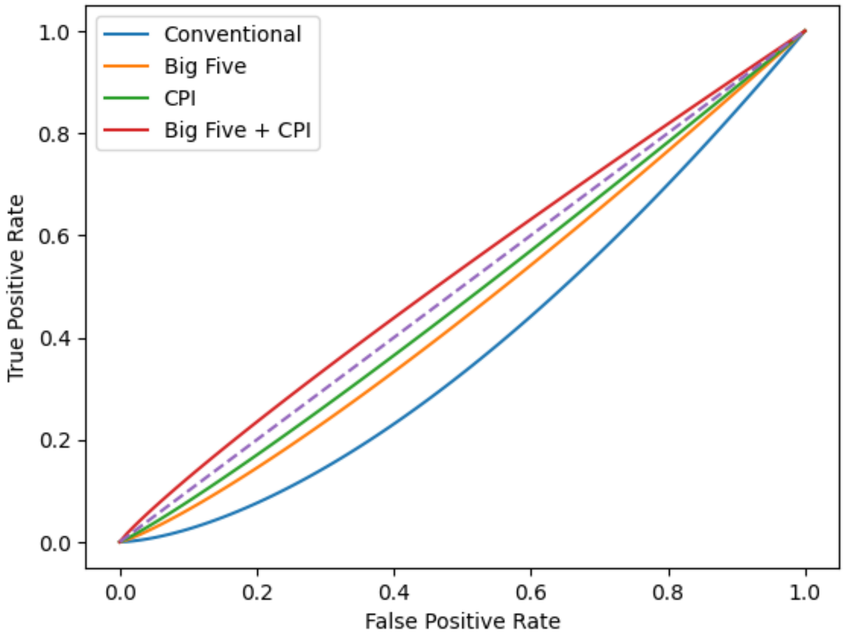


Figure 2 Performance Comparation Across Model Configurations

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

Further improvement is achieved with the inclusion of CPI indicators, where the curves continue to rise, albeit at a slightly reduced gradient. This pattern indicates that CPI dimensions provide additional behavioral granularity, particularly in modeling normative and responsibility-oriented behaviors associated with repayment compliance. The highest performance is attained by the integrated model combining both Big Five and CPI indicators. The convergence of the three performance curves at their peak values highlights the complementary nature of the two personality frameworks. This result confirms that integrating multiple psychological perspectives enables a more comprehensive representation of borrower behavior, leading to superior discrimination and overall predictive reliability.



Figur 3 ROC-style (AUC comparison)

Figure 3 presents the Receiver Operating Characteristic (ROC) curves for each model configuration, illustrating the trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR) across different decision thresholds. The diagonal reference line represents random classification performance, while curves positioned further above this line indicate stronger discriminative capability. The ROC curve corresponding to the model using conventional attributes only lies closest to the diagonal baseline, reflecting its limited ability to distinguish between default and non-default borrowers. This observation is consistent with its relatively lower AUC value, confirming that financial

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

and demographic variables alone provide insufficient behavioral resolution in online lending contexts.

The inclusion of Big Five personality indicators results in a noticeable upward shift of the ROC curve, indicating improved sensitivity across most threshold levels. This enhancement demonstrates that broad personality traits contribute meaningful behavioral signals that strengthen borrower risk differentiation. A further improvement is observed with the CPI-based model, whose ROC curve dominates the Big Five configuration across a wider range of false positive rates. This dominance suggests that CPI dimensions offer more direct insights into normative behavior, responsibility, and compliance—factors closely associated with repayment outcomes. The integrated Big Five and CPI model achieves the most convex ROC curve, consistently outperforming all other configurations. Its superior curve shape confirms the highest AUC value and indicates optimal discriminative power. This result provides strong visual evidence that combining complementary personality frameworks enables more accurate and reliable creditworthiness prediction within a decision support system.

4. CONCLUSION

This study presents a decision support model for creditworthiness prediction in online lending by integrating comparative personality indicators derived from the Big Five Personality Traits and the California Psychological Inventory (CPI). The findings demonstrate that conventional credit assessment approaches, which rely primarily on financial and demographic attributes, provide limited predictive capability when applied in digital lending environments characterized by behavioral heterogeneity. By incorporating personality-based features, the proposed model significantly enhances predictive accuracy, balance, and discriminative power. The comparative analysis reveals that both personality frameworks contribute meaningful behavioral information, albeit through different mechanisms. Big Five traits capture broad dispositional tendencies related to self-regulation and emotional stability, while CPI indicators offer more granular insights into normative behavior, responsibility, and integrity. The integrated use of both frameworks yields the highest performance across all evaluation metrics, confirming their complementary predictive value. These results provide empirical evidence that

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

behavioral and psychological constructs can be effectively operationalized within machine learning–driven decision support systems.

The inclusion of explainable artificial intelligence through SHAP-based interpretation further strengthens the practical relevance of the proposed model by enhancing transparency, trust, and governance. By providing interpretable behavioral explanations alongside predictive outcomes, the model supports more accountable and sustainable credit decision-making, particularly in fintech environments subject to regulatory and ethical scrutiny. Despite these contributions, several limitations should be acknowledged. First, this study relies on a single dataset obtained from one online lending context, which may limit the generalizability of the findings across different platforms or regulatory environments. Second, personality indicators are derived from self-reported psychometric instruments, which are subject to response bias and social desirability effects. Third, the cross-sectional research design captures borrower behavior at a single point in time and does not account for dynamic changes in personality traits or financial behavior over the loan lifecycle. These limitations highlight opportunities for future research to enhance robustness and external validity.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to Universitas Trisakti for the institutional support and academic environment that enabled the completion of this research. The authors also acknowledge the valuable facilities and scholarly resources provided by the university, which contributed to the development, analysis, and dissemination of this study.

REFERENCES

[1] C. Ofori-Acquah, C. Avortri, A. Preko, and D. Ansong, "Analysis of Ghana's National Financial Inclusion and Development Strategy: Lessons Learned," *Glob. Soc. Welf.*, vol. 10, no. 1, pp. 19–27, 2023, doi: 10.1007/s40609-022-00255-6.

[2] M.-J. Gallego-Losada, A. Montero-Navarro, E. García-Abajo, and R. Gallego-Losada, "Digital financial inclusion. Visualizing the academic literature," *Res. Int. Bus. Financ.*, vol. 64, p. 101862, 2023, doi: 10.1016/j.ribaf.2022.101862.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

[3] B. Savitha and I. T. Hawaldar, "What motivates individuals to use FinTech budgeting applications? Evidence from India during the covid-19 pandemic," *Cogent Econ. Financ.*, vol. 10, no. 1, 2022, doi: 10.1080/23322039.2022.2127482.

[4] A. Gupta, "Business and globalisation the new face of micro lending in India: A case study," *Int. J. Bus. Glob.*, vol. 12, no. 4, pp. 485–495, 2014, doi: 10.1504/IJBG.2014.062847.

[5] A. K. Tyagi, S. Kumari, N. Chidambaram, and A. Sharma, "Engineering applications of blockchain in this smart era," in *Enhancing Medical Imaging with Emerging Technologies*, National Institute of Fashion Technology, New Delhi, India: IGI Global, 2024, pp. 180–196. doi: 10.4018/979-8-3693-5261-8.ch011.

[6] G. Ahiase, D. Andriana, E. Agbemava, and B. Adonai, "Macroeconomic cyclical indicators and bank non-performing loans: does country governance matter in African countries?," *Int. J. Soc. Econ.*, 2023, doi: 10.1108/IJSE-11-2022-0729.

[7] I. Purwanto and R. Isnanto, "A Fuzzy Logic Model for Loan Recommendations in Online Lending Systems Using the California Psychological Inventory," *Ing. des Syst. d'Information*, vol. 30, no. 4, pp. 923–932, 2025, doi: 10.18280/isi.300409.

[8] H. B. Hodgdon, K. A. Lord, M. K. Suvak, L. Martin, E. C. Briggs, and K. Beserra, "Predictors of symptom severity and change among youth in trauma-informed residential care," *Child Abus. Negl.*, vol. 137, 2023, doi: 10.1016/j.chiabu.2023.106056.

[9] C. Boiteau *et al.*, "Bridging the digital divide for outpatients treated with anticancer chemotherapy: a retrospective quantitative and qualitative analysis of an adapted electronic Patient Reported Outcome program," *Support. Care Cancer*, vol. 33, no. 2, 2025, doi: 10.1007/s00520-025-09171-9.

[10] T. P. Pham, B. Popesko, S. D. Hoang, and T. B. Tran, "Impact of the Mobile Banking Application Ratings on the Vietnamese Bank Service Income," *Comp. Econ. Res.*, vol. 26, no. 1, pp. 171–186, 2023, doi: 10.18778/1508-2008.26.09.

[11] R. Kuvonchbek, J. T. Arzieva, and A. Arziev, "Designing the UzBCS Lending Platform Network Based on Blockchain Technology and Ensure Transaction Security," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, K. Y. and A. A., Eds., Tashkent State University of Economics, Tashkent, 100174, Uzbekistan: Springer Science and Business Media Deutschland GmbH, 2024, pp. 232–243. doi: 10.1007/978-3-031-60994-7_19.

I S I Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

[12] B. Raimundo and J. M. Bravo, "Credit Risk Scoring: A Stacking Generalization Approach," in *Lecture Notes in Networks and Systems*, R. A., A. H., D. G., M. F., and C. V., Eds., NOVA IMS - Universidade Nova de Lisboa, Lisbon, Portugal: Springer Science and Business Media Deutschland GmbH, 2024, pp. 382–396. doi: 10.1007/978-3-031-45642-8_38.

[13] Y. Rong, S. Liu, S. Yan, W. W. Huang, and Y. Chen, "Proposing a new loan recommendation framework for loan allocation strategies in online P2P lending," *Ind. Manag. Data Syst.*, vol. 123, no. 3, pp. 910–930, 2023, doi: 10.1108/IMDS-07-2022-0399.

[14] S. Jeon and T. Y. Kwon, "Analysis on Corporate Credit Scoring Models and Key Financial Variables Using Machine Learning," *Asian Rev. Financ. Res.*, vol. 38, no. 3, pp. 1–36, 2025, doi: 10.37197/ARFR.2025.38.3.1.

[15] J. D. Ampah *et al.*, "Performance analysis and socio-enviro-economic feasibility study of a new hybrid energy system-based decarbonization approach for coal mine sites," *Sci. Total Environ.*, vol. 854, 2023, doi: 10.1016/j.scitotenv.2022.158820.

[16] K. B. Lim, C. Z. Lo, S. F. Yeo, and C. L. Tan, "Understanding of Peer-to-Peer Lending Platform Intention: Evidence among Millennials," *Glob. Bus. Manag. Res. suppl. Spec. Issue 3rd Int. Conf. Bus. Sustain. Innov. (ICBSI 2022)*, vol. 15, no. 3s, pp. 95–110, 2023.

[17] S. Muthaiyah, L. T. P. Nguyen, Y. V Choong, and T. O. K. Zaw, "Orchestration of Federated Risk for P2P Lending Platforms: A Multi-Agent Systems (MAS) Approach," *HighTech Innov. J.*, vol. 5, no. 4, pp. 949–959, 2024, doi: 10.28991/HIJ-2024-05-04-06.

[18] S. Muthaiyah, L. T. P. Nguyen, Y. V Choong, and T. O. K. Zaw, "Risk Ordering Relation and Risk Control for P2P Lending Platforms: A Multi-Agent Systems (MAS) Approach," *Emerg. Sci. J.*, vol. 8, no. 4, pp. 1655–1665, 2024, doi: 10.28991/ESJ-2024-08-04-024.

[19] A. O. Ojo, A. A. A. Salam, C. N.-L. Tan, and C. W. Chong, "Investigating Intention To Invest in Online Peer-To-Peer Lending Platforms Among The Bottom 40 Group in Malaysia," *Interdiscip. J. Information, Knowledge, Manag.*, vol. 19, 2024, doi: 10.28945/5364.

[20] M. Ganbat *et al.*, "Effect of psychological factors on credit risk: A case study of the microlending service in mongolia," *Behav. Sci. (Basel).*, vol. 11, no. 4, 2021, doi: 10.3390/bs11040047.

[21] S. Fine, "Character Counts: Psychometric-Based Credit Scoring for Underbanked Consumers," *J. Risk Financ. Manag.*, vol. 17, no. 9, 2024, doi: 10.3390/jrfm17090423.

[22] A. Goel and S. Rastogi, "Credit scoring of small and medium enterprises: a behavioural approach," *J. Entrep. Emerg. Econ.*, vol. 15, no. 1, pp. 46–69, 2023, doi: 10.1108/JEEE-03-2021-0093.

[23] J. Leigh Wills and D. Schuldberg, "Chronic Trauma Effects on Personality Traits in Police Officers," *J. Trauma. Stress*, vol. 29, no. 2, pp. 185–189, 2016, doi: 10.1002/jts.22089.

[24] A. Alamsyah, A. A. Hafidh, and A. D. Mulya, "Innovative Credit Risk Assessment: Leveraging Social Media Data for Inclusive Credit Scoring in Indonesia's Fintech Sector," *J. Risk Financ. Manag.*, vol. 18, no. 2, 2025, doi: 10.3390/jrfm18020074.

[25] S. F. Nimmy, O. K. Hussain, R. K. Chakrabortty, F. K. Hussain, and M. Saberi, "Interpreting the antecedents of a predicted output by capturing the interdependencies among the system features and their evolution over time," *Eng. Appl. Artif. Intell.*, vol. 117, p. 105596, 2023, doi: 10.1016/j.engappai.2022.105596.

[26] C. Li, L. Wang, and H. Yang, "The optimal asset trading settlement based on Proof-of-Stake blockchains," *Decis. Support Syst.*, vol. 166, p. 113909, 2023, doi: 10.1016/j.dss.2022.113909.

[27] G. Puccetti, V. Giordano, I. Spada, F. Chiarello, and G. Fantoni, "Technology identification from patent texts: A novel named entity recognition method," *Technol. Forecast. Soc. Change*, vol. 186, p. 122160, 2023, doi: 10.1016/j.techfore.2022.122160.

[28] P. R. S. R. Junior *et al.*, "Psychometric properties of the Brazilian version of the Big Five Inventory," *Trends Psychiatry Psychother.*, vol. 45, 2023, doi: 10.47626/2237-6089-2021-0458.

[29] T. Sahin, T. Cakar, T. Bozkan, S. Ertugrul, and A. Sayar, "Modeling Consumer Creditworthiness via Psychometric Scale and Machine Learning," in *Proceedings - 7th International Conference on Computer Science and Engineering, UBMK 2022*, Mef Üniversitesi, Psikoloji, İstanbul, Turkey: Institute of Electrical and Electronics Engineers Inc., 2022, pp. 456–461. doi: 10.1109/UBMK55850.2022.9919596.

[30] I. Purwanto, R. R. Isnanto, and A. Puji Widodo, "Investigation of the Impact of the Peer-To-Peer Lending Market on the Membership Motivation of the MSME," in *E3S Web of Conferences*, 2023. doi: 10.1051/e3sconf/202344802037.

[31] M. Jay and O. P. John, "A depressive symptom scale for the California Psychological Inventory: Construct validation of the CPI-D," *Psychol. Assess.*, vol. 16, no. 3, pp. 299–309, 2004, doi: 10.1037/1040-3590.16.3.299.

ISI Journal of Information Systems and Informatics

Published By Asosiasi Doktor Sistem Informasi Indonesia

[32] D. De Silva and D. Alahakoon, "An artificial intelligence life cycle: From conception to production," *Patterns*, vol. 3, no. 6, p. 100489, 2022, doi: 10.1016/j.patter.2022.100489.

[33] A. Al Maruf, M. A.-A. Nayem, M. M. Haque, Z. M. Jiyad, A. M. O. Rashid, and F. Khanam, "A Survey on Personality Prediction," in *ACM International Conference Proceeding Series*, K. R.H., Ed., Bangladesh University of Business and Technology, Dhaka, Bangladesh: Association for Computing Machinery, 2022, pp. 407–414. doi: 10.1145/3542954.3543012.

[34] Q. Wang, R. Y. K. Lau, and K. Yang, "Does the interplay between the personality traits of CEOs and CFOs influence corporate mergers and acquisitions intensity? An econometric analysis with machine learning-based constructs," *Decis. Support Syst.*, vol. 139, p. 113424, 2020, doi: 10.1016/j.dss.2020.113424.

[35] F. A. Bernardi *et al.*, "A proposal for a set of attributes relevant for Web portal data quality: The Brazilian Rare Disease Network case," *Procedia Comput. Sci.*, vol. 219, pp. 1316–1324, 2023, doi: 10.1016/j.procs.2023.01.416.

[36] "19th Americas Conference on Information Systems, AMCIS 2013, Volume 1," in *19th Americas Conference on Information Systems, AMCIS 2013 - Hyperconnected World: Anything, Anywhere, Anytime*, 2013.

[37] R. K. Sharma, "Improving Quality of Predictive Maintenance Through Machine Learning Algorithms In Industry 4.0 Environment," *Proc. Eng. Sci.*, vol. 5, no. 1, pp. 63–72, 2023, doi: 10.24874/PES05.01.006.

[38] S. Seyedzadeh, V. Christodoulou, A. Turner, and S. Lotfian, "Optimising Manufacturing Efficiency: A Data Analytics Solution for Machine Utilisation and Production Insights," *J. Manuf. Mater. Process.*, vol. 9, no. 7, 2025, doi: 10.3390/jmmp9070210.

[39] Y. Sen, A. Z. R. Langi, A. A. Arman, and T. M. Simatupang, "Choosing and Evaluating P2P Lending with Value Engineering as a Decision Support System: An Indonesian Case Study," *Information*, vol. 15, no. 9, p. 544, 2024, doi: 10.3390/info15090544.

[40] S. Satpute *et al.*, "Loan Default Forecasting Using StackNet," in *Lecture Notes on Data Engineering and Communications Technologies*, vol. 165, Faculty of Engineering and Technology, Liverpool John Moores University, Liverpool, L3 3AF, United Kingdom: Springer Science and Business Media Deutschland GmbH, 2023, pp. 434–447. doi: 10.1007/978-981-99-0741-0_31.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

[41] R. R. Singh and V. K. Ray, "A Novel SHAP-Enhanced LightGBM Framework with Optuna Optimization for Robust Credit Risk Assessment in Financial Systems," in *Lecture Notes in Networks and Systems*, S. A., V. B., C. S.D., and P. Z., Eds., Computer Science and Engineering Department, Gautam Buddha University, Uttar Pradesh, Greater Noida, India: Springer Science and Business Media Deutschland GmbH, 2026, pp. 254–266. doi: 10.1007/978-3-032-03751-0_21.

[42] M. Al Duhayyim *et al.*, "Optimized stacked autoencoder for iot enabled financial crisis prediction model," *Comput. Mater. Contin.*, vol. 71, no. 1, pp. 1079–1094, 2022, doi: 10.32604/cmc.2022.021199.

[43] S. Ali, B. Simboh, and U. Rahmawati, "Determining Factors of Peer-to-Peer (P2P) Lending Avoidance: Empirical Evidence from Indonesia," *Gadjah Mada Int. J. Bus.*, vol. 25, no. 1, pp. 1–27, 2023, doi: 10.22146/gamaijb.68805.

[44] M. K. Hussein, A. A. Ali, M. A. Subhi, and S. M. Mohammed, "Enhancing Student Performance Evaluation Through Optimized Fuzzy Rule Techniques," *Baghdad Sci. J.*, vol. 22, no. 2, pp. 677–686, 2025, doi: 10.21123/bsj.2024.10319.

[45] H. Herrmann and B. Masawi, "Three and a half decades of artificial intelligence in banking, financial services, and insurance: A systematic evolutionary review," *Strateg. Chang.*, vol. 31, no. 6, pp. 549–569, 2022, doi: 10.1002/jsc.2525.

[46] P. N. Kemala, D. P. Koesrindartoto, and D. F. Hakam, "Advancing inclusive finance through financial technology (FinTech): peer-to-peer (P2P) and digital lending as catalyst for financial inclusion," *Digit. Financ.*, vol. 8, no. 1, 2026, doi: 10.1007/s42521-025-00166-z.

[47] L. Bunnell, K.-M. Osei-Bryson, and V. Y. Yoon, "FinPathlight: Framework for an multiagent recommender system designed to increase consumer financial capability," *Decis. Support Syst.*, vol. 134, p. 113306, 2020, doi: 10.1016/j.dss.2020.113306.

[48] D. Biswas, "Enhancing Credit Risk Prediction Through Ensemble Learning and Explainable AI Techniques: A Comprehensive Approach," in *Lecture Notes in Networks and Systems*, S. S., S. H., T. K., and K. J.V., Eds., FIS Global, Pune, India: Springer Science and Business Media Deutschland GmbH, 2025, pp. 207–225. doi: 10.1007/978-981-96-4880-1_17.

[49] M. Sanz-Guerrero and J. Arroyo, "Credit Risk Meets Large Language Models: Building a Risk Indicator from Loan Descriptions in P2P Lending," *Intel. Artif.*, vol. 28, no. 75, pp. 220–248, 2025, doi: 10.4114/intartif.vol28iss75pp220-248.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

[50] E. V Orlova, "Data Driven Design to Credit Risk Management Using Digital Footprint Intelligence," in *Proceedings - 2021 3rd International Conference on Control Systems, Mathematical Modeling, Automation and Energy Efficiency, SUMMA 2021*, Ufa State Aviation Technical University, Department of Economics and Management, Ufa, Russian Federation: Institute of Electrical and Electronics Engineers Inc., 2021, pp. 461–466. doi: 10.1109/SUMMA53307.2021.9632188.

[51] U. Chandrasekhar and N. Khare, "An intelligent tutoring system for new student model using fuzzy soft set-based hybrid optimization algorithm," *Soft Comput.*, vol. 25, no. 24, pp. 14979–14992, 2021, doi: 10.1007/s00500-021-06396-8.

[52] S. K. Abbas, "Lending by Algorithm: Fair or Flawed? An Information-Theoretic View of Credit Decision Pipelines," *SN Comput. Sci.*, vol. 6, no. 6, 2025, doi: 10.1007/s42979-025-04222-8.

[53] H. Rjoub, T. S. Adebayo, and D. Kirikkaleli, "Blockchain technology-based FinTech banking sector involvement using adaptive neuro-fuzzy-based K-nearest neighbors algorithm," *Financ. Innov.*, vol. 9, no. 1, 2023, doi: 10.1186/s40854-023-00469-3.

[54] L. T. P. Nguyen, W. Kalabeke, S. Muthaiyah, M. Y. Cheng, K. J. Hui, and H. Mohamed, "P2P lending platforms in Malaysia: What do we know?," *F1000Research*, vol. 10, 2023, doi: 10.12688/f1000research.73410.3.

[55] Y. Wang, Y. Jia, S. Fan, and J. Xiao, "Deep reinforcement learning based on balanced stratified prioritized experience replay for customer credit scoring in peer-to-peer lending," *Artif. Intell. Rev.*, vol. 57, no. 4, 2024, doi: 10.1007/s10462-023-10697-9.

[56] H.-S. Ryu and J. Min, "Innovation recipes for high use on four Fintech types: A configurational perspective," *Inf. Manag.*, vol. 62, no. 1, 2025, doi: 10.1016/j.im.2024.104058.

[57] G. Nevi, R. Montera, N. Cucari, and F. Laviola, "Integrating AI and ESG in digital platforms: New profiles of platform-based business models," *J. Eng. Technol. Manag. - JET-M*, vol. 78, 2025, doi: 10.1016/j.jengtecman.2025.101913.

[58] R. Ravina-Ripoll, E. Galvan-Vela, D. M. Sorzano-Rodríguez, and M. Ruíz-Corrales, "Mapping intrapreneurship through the dimensions of happiness at work and internal communication," *Corp. Commun.*, vol. 28, no. 2, pp. 230–248, 2023, doi: 10.1108/CCIJ-03-2022-0037.

[59] T.-H. Chiang, Y.-C. Tseng, and Y.-C. Tseng, "A multi-embedding neural model for incident video retrieval," *Pattern Recognit.*, vol. 130, p. 108807, 2022, doi: 10.1016/j.patcog.2022.108807.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

[60] Y. Tan and G. Zhao, "Multi-view representation learning with Kolmogorov-Smirnov to predict default based on imbalanced and complex dataset," *Inf. Sci. (Ny).*, vol. 596, pp. 380–394, 2022, doi: 10.1016/j.ins.2022.03.022.

[61] P. Jaulkar, H. Khandelwal, K. Sharma, R. Khandelwal, and P. Dwivedy, "Advancing Communication for the Hearing Impaired: Real-Time Sign Language Recognition and Translation," in *2025 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation, IATMSI 2025*, Ramdeobaba College of Engineering and Management, Department of Electronics and Computer Science, Nagpur, India: Institute of Electrical and Electronics Engineers Inc., 2025. doi: 10.1109/IATMSI64286.2025.10984679.

[62] M. A. H. Alias, N. Hambali, M. A. A. Aziz, M. N. Taib, and R. Jailani, "Feature selection techniques and classification algorithms for student performance classification: a review," *Int. J. Electr. Comput. Eng.*, vol. 14, no. 3, pp. 3230–3243, 2024, doi: 10.11591/ijece.v14i3.pp3230-3243.

[63] K. Kumar and M. T. U. Haider, "Blended computation of machine learning with the recurrent neural network for intra-day stock market movement prediction using a multi-level classifier," *Int. J. Comput. Appl.*, vol. 43, no. 8, pp. 733–749, 2021, doi: 10.1080/1206212X.2019.1593614.

[64] K. Niu, Z. Zhang, Y. Liu, and R. Li, "Resampling ensemble model based on data distribution for imbalanced credit risk evaluation in P2P lending," *Inf. Sci. (Ny).*, vol. 536, pp. 120–134, 2020, doi: 10.1016/j.ins.2020.05.040.

[65] Z. Zhang, C. Yu, C. Li, M. Li, and J. Hu, "Personalized Learning Style Classification and Adaptive Teaching with SRE-TransformerNet," in *Communications in Computer and Information Science*, H. D.-S., Z. C., Z. Q., and P. Y., Eds., College of Computer Science and Engineering, Shandong University of Science and Technology, Qigdao, 266590, China: Springer Science and Business Media Deutschland GmbH, 2025, pp. 321–332. doi: 10.1007/978-981-96-9986-5_27.

[66] J. Park, H. J. Na, and H. Kim, "Development of a Success Prediction Model for Crowdfunding Based on Machine Learning Reflecting ESG Information," *IEEE Access*, vol. 12, pp. 197275–197289, 2024, doi: 10.1109/ACCESS.2024.3519219.

[67] I. Met, A. Erkoc, and S. E. Seker, "Performance, Efficiency, and Target Setting for Bank Branches: Time Series With Automated Machine Learning," *IEEE Access*, vol. 11, pp. 1000–1010, 2023, doi: 10.1109/ACCESS.2022.3233529.