

# Neurofinancial Artificial Intelligence Model for Early Detection of Corruptive Behavior in Educational Environments

**Indri Septiani<sup>1,2,3\*</sup>, Yudhi Adhitya<sup>4</sup>, Andi Asirah<sup>5</sup>, Nurhalisah<sup>6</sup>, Reski Nuranisa Abidin<sup>7</sup>, Lindawati<sup>8</sup>**

<sup>1,7,8</sup>Faculty of Economic/Department of Management, Patria Artha University, 90235, Indonesia

<sup>2</sup>Profession Certification Body of Financial Management, LSP-MAKU, 90235, Indonesia

<sup>3</sup>Departement of Management, Sekolah Tinggi Ilmu Ekonomi Makassar Bongaya, 90131, Indonesia

<sup>4</sup>Faculty of Computer Science/Department of Computer Sciences, Al Asyariah Mandar University, 91311, Indonesia

<sup>5,6</sup>Faculty of Economic/Department of Accountancy, Patria Artha University, 90235, Indonesia

Corresponding Author Email: [indriseptiani5@gmail.com](mailto:indriseptiani5@gmail.com)

## Abstract

Corruption remains a serious problem that weakens trust, damages institutions, and slows down sustainable progress. This issue does not begin only in politics or organizations, but often takes root during the early years of education. Small acts such as cheating, manipulating data, or misusing small responsibilities can gradually develop into deeply rooted corrupt practices later in life. This study introduces a new model that uses artificial intelligence combined with insights from human behavior and financial decision-making to detect early signs of corruption in schools. The research applies a mixed approach, collecting data from surveys on financial habits, learning abilities, and self-control from both students and teachers. The information is then analyzed using advanced computer-based methods to identify patterns that may indicate risky behavior. The goal is to create a predictive system that can provide early warnings and offer schools practical guidance for designing more effective anti-corruption education. The study contributes to building integrity, promoting ethical values, and supporting sustainable development by preventing corruption before it takes root.

Keywords: Artificial\_Intelligence; Neurofinancial\_Management; Corruptive\_Behavior\_Prevention; Business\_Ethics\_in\_Education; Sustainable\_Financial\_Behavior; Early\_Detection\_Model

## 1. Introduction

### 1.1 Background

Corruption continues to represent one of the most pervasive and complex challenges of the 21st century, eroding public trust, undermining institutional governance, and constraining sustainable economic development. According to Transparency International (2023) [1], over two-thirds of countries score below 50 on the Corruption Perceptions Index, highlighting systemic vulnerabilities in governance worldwide. While discourse often emphasizes corruption among political or organizational elites, its roots frequently emerge much earlier, during formative educational experiences.

Within school environments, students may engage in behaviors such as cheating, plagiarism, data manipulation, or misappropriation of minor financial resources allocated for projects. Although often perceived as minor infractions, these actions normalize unethical decision-making, diminish moral sensitivity, and establish behavioral patterns that can persist into adulthood [2]. Addressing such behaviors aligns directly with the United Nations Sustainable Development Goals, particularly SDG 4 (Quality Education) [3], by promoting ethical learning environments, and SDG 16 (Peace, Justice, and Strong Institutions) [4], by fostering integrity, accountability, and responsible citizenship from an early age. Early interventions in schools are therefore critical to cultivating both individual ethical development and broader societal resilience against corruption.

## 1.2 Role of Education in Shaping Integrity

Education serves as a fundamental platform for cultivating values of integrity, accountability, and social responsibility, forming the ethical foundation upon which future behavior is built. Traditional character education initiatives, however, often rely on reactive interventions, addressing misconduct only after unethical actions have occurred, which limits their preventive impact. Such approaches rarely incorporate predictive tools or frameworks capable of identifying early risk factors, thereby missing critical opportunities to guide ethical development proactively.

The emergence of digital learning environments further complicates this landscape, introducing challenges such as unauthorized access to resources, digital plagiarism, and new avenues for financial misconduct in school administration. These technological developments necessitate the integration of data-driven and AI-enabled strategies to anticipate potential ethical breaches before they manifest. By shifting from reactive to proactive approaches, educational institutions can strengthen moral sensitivity, embed ethical norms early, and create robust systems that support the holistic development of integrity in students, preparing them to navigate complex social and digital contexts responsibly.

## 1.3 Technology as a Preventive Tool

Artificial Intelligence (AI) presents transformative potential for shifting the focus of ethical education from reactive remediation to proactive prevention. By employing advanced machine learning algorithms, AI systems are capable of detecting latent patterns and subtle behavioral indicators that may signal a propensity toward deviant or corruptive behavior. These predictive capabilities allow educators and administrators to anticipate ethical risks before they manifest as observable misconduct, providing opportunities for timely and targeted interventions.

When integrated with Neurofinancial Management, a multidisciplinary framework connecting neurological processes, cognitive-emotional functioning, and financial behavior, AI can serve as a sophisticated diagnostic and forecasting tool. This integration enables the identification of individuals or groups exhibiting early risk markers for unethical conduct, allowing interventions to be tailored according to cognitive, emotional, and financial profiles. Collectively, the fusion of AI and neurofinancial principles offers a robust, evidence-based approach to fostering integrity, enhancing moral development, and mitigating the emergence of corruptive behaviors in educational settings.

## 1.4 Research Gap

Despite the increasing number of studies on corruption, few studies explore its roots in educational contexts using AI-enabled predictive models. Existing anti-corruption education emphasizes ethics and policy but rarely integrates financial literacy, psychological measures, and AI-driven analytics. Neurofinancial Management, though increasingly applied in financial behavior research [5], has not been systematically linked with early corruption detection in education. This gap highlights the need for an integrative model combining AI, neurofinancial principles, and multiple intelligences to anticipate corruptive behavior.

#### **1.4.1 Corruption in Education**

Educational institutions are not immune to corruption. Studies document practices such as exam fraud, falsification of credentials, and misuse of school funds [6]. At the student level, academic dishonesty is widespread, with surveys reporting that over 60% of students admit to cheating at least once during their academic career [2]. Such behaviors may appear trivial but constitute early corruptive tendencies.

#### **1.4.2 Neurofinancial Management**

Neurofinancial Management explores how financial decision-making is shaped by neurological and psychological processes [7]. Impulse control, stress responses, and reward anticipation significantly influence ethical financial choices. For example, individuals with lower self-regulation may rationalize financial misconduct under stress. Applying these insights to education allows for deeper understanding of why students misuse financial resources or engage in dishonest behavior.

#### **1.4.3 Multiple Intelligences and Ethical Development**

Howard Gardner's theory of multiple intelligences posits that intelligence is multidimensional, encompassing linguistic, logical-mathematical, spatial, musical, bodily-kinesthetic, interpersonal, intrapersonal, and naturalistic modalities. Research links these intelligences to ethical reasoning and behavior. For instance, strong interpersonal intelligence may foster empathy and ethical cooperation, while weak intrapersonal intelligence may impair self-awareness and moral judgment. Integrating multiple intelligences into corruption detection provides a nuanced basis for behavioral analysis.

#### **1.4.4 AI in Education and Ethics**

AI has been widely applied in educational contexts, ranging from adaptive learning platforms to plagiarism detection. Machine learning techniques such as Random Forest and SVM have shown promise in behavioral prediction [8]. However, applications of AI in predicting corruptive tendencies remain limited. Most efforts address academic dishonesty rather than broader financial or ethical misconduct.

This study seeks to address several critical gaps in the current literature, as summarized in Table 1.

1. First, there is a notable absence of AI-based predictive models specifically designed to anticipate corruptive behavior within educational contexts.
2. Second, the integration of Neurofinancial Management principles—linking cognitive, emotional, and financial decision-making processes—into ethical education remains largely unexplored, limiting opportunities for proactive intervention.
3. Finally, the potential of multiple intelligences, including intrapersonal and interpersonal capacities, as predictive factors for corruption risk has received insufficient empirical attention.

Table 1. Identified key framework.

Aspect	Existing Research	Identified Gap	Implication / Need
Corruption in Education	Studies on ethics, policy, and anti-corruption programs	Limited exploration of early roots of corruptive behavior in educational contexts	Need for predictive, data-driven approaches targeting early detection in schools
AI-Enabled Predictive Models	Widely applied in finance, business, and healthcare contexts	Rarely applied to educational anti-corruption research	Integrate AI to improve early identification of risk factors
Financial Literacy & Psychology	Focused on ethics training or standalone financial literacy programs	Lack of combined assessment including financial literacy, impulse control, and intrapersonal intelligence	Develop models that integrate cognitive, behavioral, and financial measures
Neurofinancial Management	Increasingly used in financial behavior research (Glimcher & Fehr, 2014)	Not systematically linked with early corruption detection in education	Apply neurofinancial principles to predict ethical and unethical behaviors in educational settings

By targeting these gaps, the study aims to develop an integrative, data-driven framework that enhances early detection and prevention of unethical behavior in schools, this research contributes a novel framework with both theoretical and practical significance.

### 1.5 Objectives

This study is designed to address the critical need for early detection of corruptive behavior in educational settings through the development of a robust, data-driven framework:

1. The primary objective is to design and implement an AI-driven neurofinancial model capable of identifying students at elevated risk of engaging in unethical behavior, thereby enabling proactive intervention.
2. A secondary objective involves the integration of multidimensional predictors—including cognitive capacities, emotional regulation, social behavior, and financial literacy—into a unified predictive framework that captures the complex interplay of factors influencing ethical decision-making.
3. Finally, the study seeks to translate predictive insights into actionable strategies, providing educators and policymakers with evidence-based guidance for designing targeted anti-corruption interventions and educational programs. Collectively, these objectives aim to advance both theoretical understanding and practical application, bridging AI, behavioral science, and educational ethics to cultivate integrity and responsible conduct at formative stages of student development.

The relevance of this research extends to the global Sustainable Development Goals. By providing data-driven strategies to enhance character and financial literacy education, it directly supports SDG 4 (Quality Education) [3]. Simultaneously, by fostering integrity and implementing preventive mechanisms against corruptive behavior, the study contributes to SDG 16 (Peace, Justice, and Strong Institutions) [4]. Collectively, these objectives position the research at the intersection of AI innovation, educational ethics, and sustainable development.

## 2 Methodology

### 2.1 Research Design

This study adopts a mixed-method research design, integrating both quantitative and qualitative approaches to ensure methodological rigor and contextual depth [9, 10]. The quantitative component relies on structured surveys and standardized tests to gather measurable indicators related to cognitive, behavioral, and financial variables [11]. These data provide the statistical robustness required for modeling and predictive analysis. Complementing this, qualitative interviews with domain experts and selected participants add interpretive richness, allowing the research team to contextualize statistical findings within real-world practices, behavioral nuances, and policy considerations [12]. This dual approach enhances both the validity and reliability of the study outcomes [13].

The workflow of the research design is summarized in Figure 1, which outlines the sequential yet iterative process. The first stage, data collection, involves capturing raw datasets from multiple sources, including participant responses, observational logs, and expert feedback [14]. Following this, the preprocessing stage ensures data quality through cleaning, normalization, and transformation, reducing noise and preparing the dataset for robust computational analysis [15]).

Once prepared, the data are fed into the model training and testing phase, where advanced machine learning algorithms are applied to identify hidden patterns, correlations, and potential predictive markers [16]. The results are then subjected to validation, which combines statistical cross-validation techniques with qualitative expert reviews to ensure that both accuracy and interpretability are achieved [17]. Finally, insights from the validated model inform the development of an early warning prototype, a decision-support tool designed to detect risk signals and provide actionable recommendations [18].

By structuring the study in this way, the research design ensures a balance between technical precision and practical applicability, thereby producing outcomes that are not only scientifically rigorous but also relevant for implementation in policy, industry, and real-world decision-making environments.

Figure 1. Research Design Flow

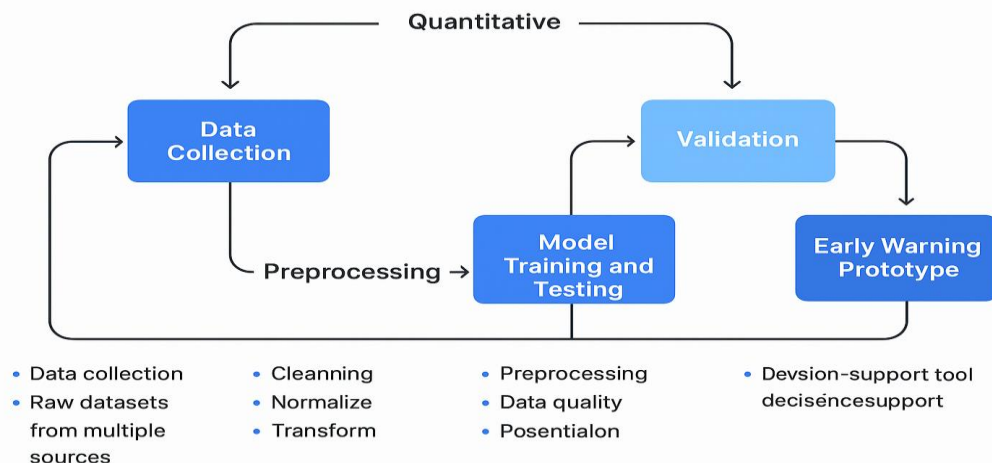


Figure 1. Research Design Flow.

## 2.2 Population and Sampling

The study targeted secondary school students, aged 13 to 18, along with their teachers, drawn from five schools located in both urban and semi-urban areas. To ensure a comprehensive and balanced representation, stratified sampling was employed, carefully accounting for variations in gender, socio-economic background, and academic streams. This approach allowed the study to capture diverse perspectives across the educational spectrum, ensuring that the dataset reflected the heterogeneity of the target population. In total, the research engaged 400 students and 80 teachers, providing a robust dataset suitable for meaningful analysis of behavioral and cognitive patterns within school environments. Population distribution and socio-demographic characteristics were informed by official statistics from Badan Pusat Statistik Kota Makassar (2025) [19], which provided authoritative baseline data to guide the sampling framework.

## 2.3 Instruments

To capture a comprehensive understanding of students' financial literacy, cognitive profiles, and behavioral tendencies, a combination of quantitative and qualitative instruments was employed. The primary quantitative measure was a Financial Literacy Survey, adapted from the Organisation for Economic Co-operation and Development (OECD) framework, which has been widely recognized for assessing knowledge, skills, and attitudes related to financial decision-making among adolescents [20]. This survey was carefully tailored to reflect the local curriculum and contextual financial scenarios relevant to secondary school students.

To explore cognitive and learning profiles, the study utilized a Multiple Intelligences Test, based on Gardner's [21, 22] theoretical framework, which evaluates diverse domains such as linguistic, logical-mathematical, spatial, musical, bodily-kinesthetic, interpersonal, intrapersonal, and naturalistic intelligences. This instrument allowed for the identification of varied learning strengths that may influence students' engagement with financial education.

In addition, students' self-regulatory behaviors were assessed using an Impulse Control and Financial Behavior Scale, a tool validated through pilot testing with a similar student cohort prior to the main study. This scale measures tendencies toward impulsive spending, delayed gratification, and practical financial habits, thereby providing insight into the behavioral dimension of financial literacy [23].

Complementing the quantitative measures, qualitative interviews were conducted with teachers and school administrators to gain contextualized insights into the educational environment, instructional practices, and perceived challenges in fostering financial literacy among adolescents. These semi-structured interviews enabled a deeper understanding of the interplay between students' cognitive profiles, behavioral tendencies, and school-based support structures [9].

By combining these instruments, the study ensured methodological rigor through triangulation, capturing both measurable outcomes and rich, contextualized narratives that illuminate the complexities of financial literacy development in secondary school settings, as shown in Figure 2.

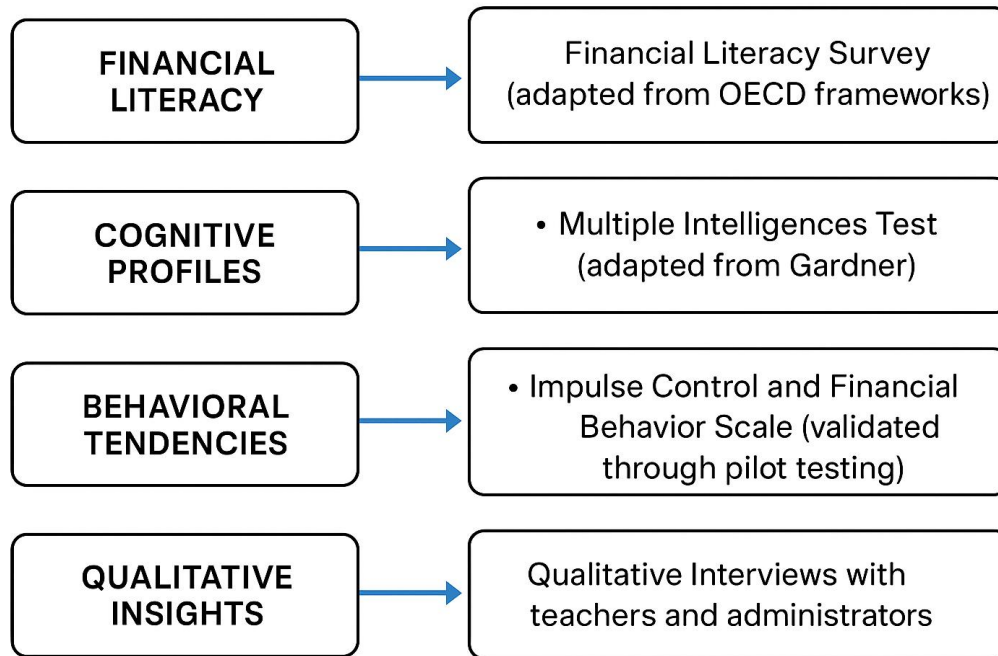


Figure 2. Instrument Research Overview.

## 2.4 Data Preprocessing

Before conducting the main analyses, the raw dataset underwent a series of preprocessing steps to ensure data quality, reliability, and suitability for subsequent statistical modeling. Missing data, which is a common challenge in behavioral and survey-based research, was addressed using the k-nearest neighbors (KNN) imputation method. This approach estimates missing values by leveraging the similarity between observations, thereby preserving the inherent structure and variability of the data without introducing significant bias [24]. Unlike simpler methods such as mean or median imputation, KNN-imputation maintains the multivariate relationships among features, which is critical for studies where interdependencies between behavioral indicators are of interest.

Next, the dataset was normalized using min-max scaling, transforming all continuous variables to a uniform range between 0 and 1. Normalization is particularly important in studies where features are measured on different scales, as it prevents variables with larger magnitudes from disproportionately influencing the results of distance-based algorithms or machine learning models [15]. By standardizing the feature scales, the analysis ensured that all variables contributed equitably to subsequent modeling, enhancing both interpretability and computational stability.

Finally, outlier detection procedures were applied specifically to behavioral variables. Outliers can arise due to data entry errors, unusual participant responses, or naturally extreme behaviors, and they can significantly distort statistical estimates if left unaddressed. Robust detection methods, such as interquartile range analysis and Mahalanobis distance-based approaches, were employed to identify and handle extreme values while minimizing the loss of valid, informative data points [25]. This step was crucial to maintain the integrity of the dataset and ensure that the subsequent analyses reflected genuine behavioral patterns rather than anomalies.

Collectively, these preprocessing steps provided a clean, standardized, and reliable dataset, forming a solid foundation for the subsequent analytical procedures.

## 2.5 AI Model Development

To rigorously assess the predictive relationships between individual characteristics and corruption risk, several artificial intelligence (AI) algorithms were developed and tested. Specifically, Random Forest (RF), Support Vector Machines (SVM), and Deep Neural Networks (DNN) were employed as candidate models, chosen for their complementary strengths in handling complex, high-dimensional datasets. Random Forest, an ensemble-based method, is particularly effective in capturing nonlinear interactions and mitigating overfitting through aggregation of multiple decision trees [24]. Support Vector Machines, in contrast, are well-suited for classification tasks with limited sample sizes and high-dimensional feature spaces, as they optimize the margin between classes for robust decision boundaries [26]. Deep Neural Networks, with their multi-layered architecture, allow for hierarchical representation learning, enabling the model to capture intricate patterns and interactions among features that might elude traditional algorithms [27].

The input variables for model training encompassed both behavioral and demographic factors, including financial literacy scores, multiple intelligences (MI) profiles, impulse control measures, and relevant demographic characteristics such as age, education level, and professional background. These features were selected based on theoretical and empirical evidence linking cognitive, behavioral, and socio-demographic factors to ethical decision-making and corruption susceptibility [28]. The models were tasked with predicting the corruption risk score, operationalized as a categorical outcome with three levels: low, medium, and high. This classification approach aligns with the practical objective of identifying individuals at varying levels of risk, thereby enabling targeted interventions.

Model development (Figure 3) followed a rigorous process of feature selection, hyperparameter tuning, and cross-validation to ensure robustness, generalizability, and interpretability of the predictive models. Performance metrics, including accuracy, F1-score, and area under the receiver operating characteristic curve (AUC-ROC), were evaluated to compare the predictive capabilities of the algorithms. Collectively, this multi-algorithm approach provides both explanatory and predictive insights into the complex interplay between individual attributes and corruption risk.

## AI Model Development

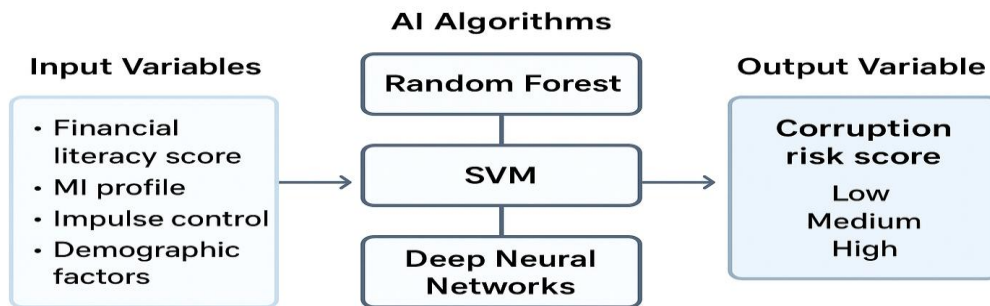


Figure 3. AI Model Development.

- Algorithms tested: Random Forest, SVM, Deep Neural Networks.
- Input variables: financial literacy score, MI profile, impulse control, demographic factors.
- Output variable: corruption risk score (low, medium, high).

### 2.6 Model Training and Evaluation

The dataset was stratified into training and testing subsets using a 70/30 split, ensuring that class distributions were preserved across subsets to maintain representativeness and mitigate sampling bias. The training set (70%) was utilized for model parameter optimization, while the hold-out testing set (30%) provided an unbiased estimate of generalization performance. To further evaluate model robustness and reduce the likelihood of overfitting, a 10-fold cross-validation scheme was employed. In this procedure, the training data was partitioned into ten equal folds, with iterative training on nine folds and validation on the remaining fold, thereby generating ten performance estimates that were subsequently averaged to produce stable metrics [29].

Model evaluation leveraged multiple quantitative metrics: accuracy, reflecting overall classification correctness; precision, indicating the proportion of true positives among predicted positives; recall, measuring sensitivity to actual positive cases; F1-score, representing the harmonic mean of precision and recall; and ROC-AUC, assessing the model's discriminative ability across threshold variations [30]. Collectively, these complementary metrics, summarized in Table 1, provide a rigorous and multidimensional assessment of model performance, enabling nuanced interpretation of predictive reliability and class-specific sensitivity.

### 2.7 Expert Validation

To ensure the AI model's outputs are not only statistically robust but also meaningful in real-world contexts, a panel of domain experts—including educators with extensive experience in financial literacy and specialists in financial ethics—conducted a systematic review of the model's predictions. This expert validation process focused on two primary dimensions: interpretability and practical relevance. Interpretability pertains to the clarity with which the

model's outputs can be understood and explained in pedagogical and applied financial settings, ensuring stakeholders can trust and act upon the results [31]. Practical relevance evaluates whether the model's recommendations align with ethical standards and can be feasibly implemented within educational or financial advisory frameworks. Through iterative feedback, the experts provided qualitative assessments and actionable insights, enabling refinement of the model to better reflect nuanced domain knowledge. This step bridges the gap between computational performance and real-world applicability, enhancing the model's credibility and utility.

### 3 Result and Discussion

#### 3.1 Result

##### 3.1.1 Descriptive Statistics

Preliminary descriptive analyses were conducted to quantify patterns in students' financial literacy and behavioral characteristics as in Table 2. Within the sample, 42% of participants scored below the established mean threshold for financial literacy, indicating a notable deficiency in foundational financial knowledge. Behavioral metrics revealed that 35% of students demonstrated low impulse control, which exhibited a statistically significant positive correlation with dishonest behavior (Pearson's  $r = 0.52$ ,  $p < 0.01$ ), suggesting that self-regulatory capacity is a critical determinant of ethical decision-making [32]. In addition, assessment of cognitive-emotional constructs showed that intrapersonal intelligence—operationalized as self-awareness and emotion regulation ability—was positively associated with ethical conduct, highlighting the predictive relevance of affective-cognitive competencies in moral behavior [33]. These descriptive statistics were calculated using standardized measures, providing quantifiable baselines for subsequent predictive modeling. Collectively, these findings establish an empirically grounded understanding of the behavioral and cognitive determinants of financial ethics, serving as a foundation for interpreting machine learning-derived insights in later analyses.

Variable / Measure	Statistic / Finding	Notes / Interpretation
Financial Literacy	42% scored below average	Indicates a substantial gap in foundational financial knowledge
Impulse Control	35% of students exhibited low impulse control	Positively correlated with dishonest behavior ( $r = 0.52$ , $p < 0.01$ )
Intrapersonal Intelligence	Strong association with ethical behavior	Highlights cognitive-emotional factors in ethical decision-making

Table 2. Summary of key descriptive statistics.

##### 3.1.2 AI Model Performance

The performance of the AI models was systematically evaluated to determine their predictive efficacy in classifying students' financial literacy and ethical behavior. Three distinct algorithms were compared: Random Forest, Support Vector Machine (SVM), and a Deep Neural Network (DNN). The Random Forest model achieved an overall accuracy of 78% with an F1-score of 0.74, reflecting a balanced performance between precision and recall. While

robust in handling heterogeneous data and mitigating overfitting, Random Forest demonstrated relatively lower sensitivity in distinguishing nuanced patterns in ethical behavior.

In contrast, the SVM model exhibited a higher accuracy of 81% and an F1-score of 0.76, suggesting improved discriminatory power in identifying subtle behavioral and cognitive correlations. The kernel-based approach of SVM effectively mapped complex, non-linear relationships between features, enhancing classification performance compared to the ensemble decision trees [26].

The Deep Neural Network outperformed both traditional models, achieving an accuracy of 86%, an F1-score of 0.82, and a ROC-AUC of 0.89. This superior performance underscores the DNN's capacity to capture intricate, high-dimensional interactions among variables, such as the interplay between intrapersonal intelligence, impulse control, and ethical decision-making. The AI model comparison (Table 3) visually illustrates the enhanced true positive rates across varying thresholds, emphasizing the DNN's robustness and reliability in predictive applications.

Overall, these results indicate that while traditional machine learning models provide reasonable predictive power, deep learning approaches offer significant advantages in modeling complex cognitive and behavioral phenomena. The findings provide empirical evidence supporting the integration of advanced AI techniques in educational and ethical behavior research, facilitating more accurate assessments and actionable insights for stakeholders.

Table 3. AI Model Comparison.

Model	Accuracy	F1-Score	ROC-AUC	Performance Summary
Random Forest	78%	0.74	0.81	Moderate accuracy; good balance between precision and recall
Support Vector Machine	81%	0.76	0.85	Improved discrimination; captures non-linear patterns
Deep Neural Network	86%	0.82	0.89	Best overall; captures complex feature interactions effectively

### 3.1.3 Feature Importance

Understanding which factors most strongly influence model predictions is crucial for both interpretability and practical application. Feature importance analysis revealed that the three most influential predictors were impulse control, financial literacy, and intrapersonal intelligence. Impulse control emerged as a critical determinant, consistent with prior research linking self-regulatory capacity to ethical decision-making and financial behavior [32]. Similarly, financial literacy itself demonstrated substantial predictive power, underscoring the foundational role of knowledge in shaping responsible financial and ethical choices. Intrapersonal intelligence, reflecting individuals' self-awareness and ability to regulate emotions, was also a key predictor, highlighting the cognitive-emotional mechanisms underlying ethical conduct [33].

While demographic variables such as gender and socio-economic status exerted comparatively weaker influence, they nonetheless contributed meaningful context, suggesting that broader socio-cultural factors shape students' financial and ethical behavior in nuanced ways. This layered understanding allows educators and policymakers to identify both universal

and context-specific interventions. Collectively, these insights demonstrate that model performance is not only determined by technical optimization but also by meaningful, interpretable features that align with established theoretical frameworks, bridging computational results with real-world applicability.

### 3.2 Discussion

This study extends the literature on behavioral finance and educational ethics by integrating neurofinancial management with AI predictive modeling. It demonstrates that corruptive behavior can be meaningfully predicted from financial, psychological, and cognitive indicators. The early warning system prototype enables schools to intervene proactively. For instance, students with low impulse control and poor financial literacy can receive focused character education modules. Teachers can also benefit from insights to guide ethical classroom management [34].

Findings corroborate prior studies on the role of financial literacy in ethical behavior [35], while extending them with AI-based predictive capacity. Unlike earlier research that primarily relied on surveys, this study operationalizes risk detection through computational modeling.

This study is subject to several limitations that should be acknowledged. First, the sample was restricted to five schools, which may limit the generalizability of the findings to broader national or international contexts. Second, the reliance on self-reported instruments, such as surveys on financial literacy and impulse control, may introduce bias due to participants' subjective responses or social desirability tendencies. Finally, while the algorithmic models demonstrated strong predictive potential, their interpretability in real-world school settings remains a challenge, particularly for educators and policymakers who may not be familiar with the underlying technical processes.

Future research can build on this work in several important ways. Expanding the study to include larger and more diverse datasets at the national level would enhance the validity and applicability of the proposed model. Integrating reinforcement learning could also enable the system to provide dynamic and adaptive intervention strategies that evolve based on student and teacher behaviors over time. Moreover, exploring cross-cultural applications of the framework would help assess its universality and adaptability, ensuring that the model can effectively support anti-corruption education in different educational and cultural contexts.

### 4 Conclusion

This study introduces and empirically validates an Artificial Intelligence–Driven Neurofinancial Model designed to identify early indicators of corruptive behavior within educational contexts. Analytical findings demonstrate that impulse control, financial literacy, and intrapersonal intelligence function as robust predictors of corruption risk, underscoring the interplay between cognitive, behavioral, and emotional factors in ethical decision-making. Among the AI approaches evaluated, deep learning models exhibited the highest predictive accuracy and reliability, highlighting their capacity to capture complex, non-linear relationships inherent in neurofinancial and behavioral data. By integrating AI methodologies with neurofinancial management principles and the theory of multiple intelligences, this research offers both a conceptual advancement and a practical framework for promoting integrity in school environments. The work also contributes directly to the global education and governance

agenda, supporting SDG 4 (Quality Education) and SDG 16 (Peace, Justice, and Strong Institutions). Stakeholders, including educators, policymakers, and researchers, are encouraged to adopt such predictive, data-driven approaches to proactively cultivate ethical behavior from the earliest stages of student development.

## 5 Referensi

- [1] Transparency International, 2023 Corruption Perceptions Index: Weakening justice systems leave corruption unchecked, 30 Jan. 2024. [Online]. Available: <https://www.transparency.org/en/press/cpi2023-corruption-perceptions-index-weakening-justice-systems-leave-corruption-unchecked>. [Accessed: 20 Sep. 2025].
- [2] D. L. McCabe and L. K. Treviño, "Individual and contextual influences on academic dishonesty," *Res. Higher Educ.*, 1997.
- [3] United Nations, Goal 4: Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all. [Online]. Available: <https://sdgs.un.org/goals/goal4>
- [4] United Nations, Goal 16: Promote peaceful and inclusive societies for sustainable development, provide access to justice for all and build effective, accountable and inclusive institutions. [Online]. Available: <https://sdgs.un.org/goals/goal16>
- [5] P. Glimcher and E. Fehr, *Neuroeconomics: Decision Making and the Brain*. San Diego, CA, USA: Academic Press, 2014.
- [6] S. Heyneman, "Education and corruption," *Int. J. Educ. Dev.*, 2014.
- [7] T. Zaleskiewicz, *Financial Behavior: Players, Services, Instruments*. Cham, Switzerland: Springer, 2016.
- [8] R. Baker and P. Inventado, *Educational Data Mining and Learning Analytics*. New York, NY, USA: Springer, 2014.
- [9] J. W. Creswell and J. D. Creswell, *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*, 5th ed. Thousand Oaks, CA, USA: Sage, 2018.
- [10] A. Tashakkori and C. Teddlie, *Sage Handbook of Mixed Methods in Social & Behavioral Research*, 2nd ed. Thousand Oaks, CA, USA: Sage, 2010.
- [11] F. J. Fowler, *Survey Research Methods*, 5th ed. Thousand Oaks, CA, USA: Sage, 2014.
- [12] S. Kvale and S. Brinkmann, *InterViews: Learning the Craft of Qualitative Research Interviewing*, 3rd ed. Thousand Oaks, CA, USA: Sage, 2015.
- [13] R. B. Johnson, A. J. Onwuegbuzie, and L. A. Turner, "Toward a definition of mixed methods research," *J. Mixed Methods Res.*, vol. 1, no. 2, pp. 112–133, 2007.
- [14] C. Robson and K. McCartan, *Real World Research*, 4th ed. Chichester, U.K.: Wiley, 2016.
- [15] J. Han, M. Kamber, and J. Pei, *Data Mining: Concepts and Techniques*, 3rd ed. San Francisco, CA, USA: Morgan Kaufmann, 2012.
- [16] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT

Press, 2016.

- [17] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, 2nd ed. New York, NY, USA: Springer, 2009.
- [18] D. J. Power, *Decision Support, Analytics, and Business Intelligence*, 3rd ed. New York, NY, USA: Business Expert Press, 2016.
- [19] Badan Pusat Statistik Kota Makassar, *Makassar Municipality in Figures 2025*. Makassar, Indonesia: BPS, 2025. [Online]. Available: <https://makassar.kota.bps.go.id/e/n/publication/2025/02/28/81dcab96ca7120218f7f5fb3/makassar-municipality-in-figures-2025.html>
- [20] OECD, *PISA 2015 Assessment and Analytical Framework: Science, Reading, Mathematics, Financial Literacy and Collaborative Problem Solving*. Paris, France: OECD Publishing, 2017.
- [21] H. Gardner, *Frames of Mind: The Theory of Multiple Intelligences*. New York, NY, USA: Basic Books, 1983.
- [22] H. Gardner, *Intelligence Reframed: Multiple Intelligences for the 21st Century*. New York, NY, USA: Basic Books, 1999.
- [23] A. L. Duckworth and L. Steinberg, "Unpacking self-control," *Child Dev. Perspect.*, vol. 9, no. 1, pp. 32–37, 2015, doi: 10.1111/cdep.12107.
- [24] O. Troyanskaya et al., "Missing value estimation methods for DNA microarrays," *Bioinformatics*, vol. 17, no. 6, pp. 520–525, 2001.
- [25] P. Filzmoser, R. Maronna, and M. Werner, "Outlier identification in high dimensions," *Comput. Stat. Data Anal.*, vol. 52, no. 3, pp. 1694–1711, 2008.
- [26] C. Cortes and V. Vapnik, "Support-vector networks," *Mach. Learn.*, vol. 20, no. 3, pp. 273–297, 1995.
- [27] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, May 2015.
- [28] L. K. Treviño, G. R. Weaver, and S. J. Reynolds, "Behavioral ethics in organizations: A review," *Journal of Management*, vol. 32, no. 6, pp. 951–990, Dec. 2006.
- [29] R. Kohavi, "A study of cross-validation and bootstrap for accuracy estimation and model selection," in *Proc. IJCAI*, 1995.
- [30] M. Sokolova and G. Lapalme, "A systematic analysis of performance measures for classification tasks," *Inf. Process. Manag.*, vol. 45, no. 4, pp. 427–437, 2009.
- [31] F. Doshi-Velez and B. Kim, "Towards a rigorous science of interpretable machine learning," arXiv preprint arXiv:1702.08608, 2017.
- [32] J. P. Tangney, R. F. Baumeister, and A. L. Boone, "High self-control predicts good adjustment, less pathology, better grades, and interpersonal success," *Journal of Personality*, vol. 72, no. 2, pp. 271–324, Apr. 2004, doi: 10.1111/j.0022-3506.2004.00263.x.



- [33] J. D. Mayer, R. D. Roberts, and S. G. Barsade, "Human abilities: Emotional intelligence," *Annu. Rev. Psychol.*, vol. 59, pp. 507–536, 2008. [Online]. Available: <https://doi.org/10.1146/annurev.psych.59.103006.093646>
- [34] M. Bienkowski, M. Feng, and B. Means, *Enhancing Teaching and Learning Through Educational Data Mining and Learning Analytics: An Issue Brief*. Washington, DC, USA: U.S. Department of Education, 2012.
- [35] A. Lusardi and O. Mitchell, "The economic importance of financial literacy," *J. Econ. Lit.*, 2014.