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Levels of Disclosure in Financial Reports According to the Financial Literacy of Their Users and the Mechanism for Determining Them by Artificial Intelligence Techniques

Muhammad Ali Jaafar
Faculty of Administration and Economy, Kerbala University, Iraq.
Email : muhammed.a@uokerbala.edu.iq

Abstract. *The research aimed to analyze the relationship between the financial literacy of financial report users and the required level of disclosure, and to propose an intelligent mechanism based on artificial intelligence techniques to customize report content. The research variables were identified as: financial literacy (high, medium, low) and disclosure level (basic, medium, advanced), with a study of the effects of age and educational level. The research adopted a mixed methodology (descriptive and analytical) using machine learning models (Random Forest) and analysis of a questionnaire consisting of 15 questions. The research sample included 150 participants from Baghdad Bank and Asia Islamic Bank of Iraq, with 155 questionnaires distributed (electronically and on paper), excluding 5 incomplete questionnaires. The results showed a strong positive correlation between financial literacy and the level of disclosure, where 75% of those with high financial literacy preferred advanced reports. The artificial intelligence model also recorded an accuracy of 82% in predicting the optimal level of disclosure. The research recommended adopting intelligent customizable financial reports through artificial intelligence and enhancing users' financial literacy to improve decision quality.*

Keywords: *Artificial Intelligence, Financial Disclosure, Financial Literacy, Report Customization, Machine Learning.*

1. INTRODUCTION

Amid the rapid developments in the financial and banking sector, there is an increasing need to enhance the transparency of financial reporting and align it with the cognitive abilities of users to ensure the effectiveness of economic decision-making. Studies indicate a significant disparity in the levels of financial disclosure among institutions, which may lead to a gap between the presented content and users' actual understanding—especially given the varying levels of financial literacy among them. In this context, the current study seeks to explore the relationship between users' financial literacy and their disclosure expectations, while highlighting the pivotal role of artificial intelligence (AI) in designing intelligent, customizable financial reports. This research aims to achieve two main objectives:

First, to analyze the impact of financial literacy (classified as high, medium, or low) on users' expectations regarding disclosure levels (basic, intermediate, advanced).

Second, to propose an AI-based model capable of automatically adapting the content of financial reports to the demographic and cognitive characteristics of users.

To achieve these objectives, the study employed a mixed-method approach combining statistical analysis of a survey involving 150 participants from Bank of Baghdad and Asia Islamic Bank of Iraq, and the application of machine learning algorithms (such as Random Forest) to analyze data and predict the optimal disclosure level.

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This study derives its worth in its effort to fill the gap between traditional financial disclosure needs and the variety of users' needs, and to offer novel solutions through the employment of latest technologies in terms of fostering more transparency and efficiency in banking. In addition, it opens a window to massive applications of AI in money tool design interactive adaptation to the evolution of financial literacy in society.

The research presents a comprehensive framework, starting with a theoretical review of the concepts of financial disclosure and financial literacy, followed by a survey of previous studies, and concluding with practical applications and AI models—making it a key reference for those interested in advancing financial disclosure mechanisms in the digital era.

2. LITERATURE REVIEW

Financial Disclosure According to Users

Al-**Juhani, A. (2021). The Effect of the Level of Financial Disclosure on Investor Decisions in the Saudi Financial Market.**

This study aimed to analyze the effect of the level of financial disclosure on investor decisions in the Saudi financial market. A questionnaire was distributed to 200 investors, and statistical analysis was conducted using SPSS. The results showed that 65% of financially literate individuals demanded advanced financial reports, while 80% of those with low financial literacy preferred basic simplified reports. The study recommended designing multi-level financial reports to suit the diversity of users' financial literacy.

Johnson, R. (2021). The Impact of Financial Disclosure Levels on Investor Decision-Making.

The study aimed to analyze the impact of financial disclosure levels on institutional investor confidence in the United States, using a quantitative analysis of 500 financial reports via multiple regression models. The results showed a 30% increase in institutional investor confidence when using advanced reports, and a 15% decline in confidence with basic, unexplained reports. The study recommended adopting advanced disclosure standards to support institutional investor decisions.

Financial Literacy and Its Impact on Financial Decision-Making

Al-Khawalda, R. (2020). Financial Literacy and Its Relationship to Investment Decision-Making in Jordan. Journal of Economic Studies, 15(4), 85–100.

The study aimed to examine the relationship between financial literacy and investment decision-making in Jordan, using a 20-question survey distributed to 300 participants. A regression analysis was conducted to identify influencing factors. The results showed that 70% of individuals with moderate financial literacy preferred investing in real estate rather than stocks, and 40% of participants did not understand terms like "investment diversification." The study recommended developing financial awareness programs to improve understanding of investment concepts.

Klapper, L., & Panos, G. (2022). The Role of Financial Education in Reducing Debt in Europe.

This study aimed to evaluate the effect of educational programs on reducing personal debt in Germany through a longitudinal study involving 1,000 households, comparing data before and after the educational intervention. The results showed a 25% reduction in average household debt, and a 40% improvement in understanding terms like "compound interest." The study recommended integrating financial education programs into school curricula.

Applications of Artificial Intelligence in Enhancing Financial Data Presentation

Al-Suhaili, K. (2023). Applications of Artificial Intelligence in Enhancing Financial Reporting: A Case Study of Al Rajhi Bank. Journal of Financial Information Technology, 5(2), 65–80.

The study aimed to evaluate the effectiveness of AI in improving credit risk prediction accuracy at Al Rajhi Bank. The Random Forest algorithm was applied to the data of 5,000 clients, and the results were compared with traditional methods. The findings showed a 25% increase in prediction accuracy for default risk, and a reduction in data analysis time from 10 days to 3 hours. The study recommended adopting AI technologies in financial institutions to enhance efficiency.

Dastile, X., Celik, T., & Potsane, M. (2021). Machine Learning for Fraud Detection in Financial Statements.

This study explored the role of AI in detecting financial fraud by applying the Random Forest algorithm to 10,000 historical financial transactions. The study achieved 92% accuracy in identifying fraudulent transactions and reduced operational costs by 18%. The study recommended integrating machine learning models into financial control systems.

3. THEORETICAL FRAMEWORK

Financial Disclosure: Concept and Levels

Definition: Financial disclosure is the process of presenting financial and non-financial information related to an entity to internal and external users, with the aim of enhancing transparency and enabling stakeholders to make informed decisions. (Hendriksen & Van Breda, 2020, p. 45). It includes fundamental financial statements such as balance sheets and income statements, as well as explanatory notes that clarify accounting policies, risks, and investments. Financial disclosure is a fundamental pillar for building trust between institutions and investors, creditors, and regulatory bodies. (Al-Htaybat & von Alberti-Alhtaybat, 2017, p. 112).

Disclosure Levels:

Financial disclosure can be classified into three levels based on the depth and detail of the information provided:

- **Basic Disclosure:** Includes the legally required minimum of information, such as basic financial statements without additional details. It targets non-specialist users like small investors. (Bushman, 2003, p. 78)
- **Intermediate Disclosure:** Goes beyond legal requirements to include brief explanations of accounting policies, initial financial performance analysis, and operational risk assessments. It is aimed at users with intermediate financial knowledge, such as financial advisors. (Healy & Palepu, 2001, p. 406)**.**
- **Advanced Disclosure:** Offers comprehensive details, including sustainability reports, future scenario analyses, ESG (Environmental, Social, and Governance) reports, and industry benchmark comparisons. It is tailored to financial analysts and experts making strategic decisions. (Eccles & Krzus, 2010, p. 93)**.**

Disclosure Standards – IFRS vs. GAAP:

The International Financial Reporting Standards (IFRS) and the Generally Accepted Accounting Principles (GAAP) are the two most common frameworks for regulating financial disclosure globally:

- **IFRS:** Issued by the International Accounting Standards Board (IASB), IFRS aims to harmonize accounting practices worldwide, focusing on general principles rather than detailed rules. This allows reports to be adapted to diverse economic contexts. For instance, IFRS requires the disclosure of fair value for intangible assets (IAS 38). (Deloitte, 2023, p. 7)**.**
- **GAAP:** Applied in the United States, GAAP is known for its detailed rules that minimize subjective estimates. It mandates disclosure of specifics such as depreciation methods for fixed assets and prefers using historical cost in asset valuation. (FASB, 2020, p. 22)**.**

Table 1. Comparison Between IFRS and GAAP in Financial Disclosure

GAAP	IFRS	Aspect
Detailed and strict rules	General and flexible principles	**Focus**
Focuses on historical cost	Encourages use of fair value	**Valuation**
Limited to standards such as ASC 275	Mandatory in management reports	**Risk Disclosure**
Primarily the United States	About 140 countries	**Geographic Application**

(Source: PWC, 2022, p. 15; KPMG, 2021, p. 9)

Institutions face challenges in balancing inclusivity and clarity in disclosure. Investors are demanding more transparency regarding non-financial risks such as climate change (TCFD, 2017, p. 4), while excessive information may overwhelm users with limited expertise. Here, modern technologies like artificial intelligence play an important role in tailoring reports to meet the needs of diverse users (Beattie, 2014, p. 88).

Users' Financial Literacy

Definition of Financial Literacy: Financial literacy refers to the ability to understand and use basic financial concepts to make effective financial decisions, such as managing debt, saving, investing, and assessing risk (Lusardi & Mitchell, 2023, p. 5). It encompasses three key skills: Financial knowledge, which involves understanding terms and concepts such as compound interest and inflation. Financial behavior, which reflects the practical application of knowledge such as budgeting. Financial confidence, which enables individuals to deal wisely with financial products. Financial literacy is considered a foundation for promoting financial inclusion and empowering individuals to face economic challenges (Huston, 2022, p. 34).

Classification of Users Based on Financial Literacy

Individuals can be classified into three main categories based on their proficiency in financial skills:

- **High Financial Literacy:** Individuals in this category have a deep understanding of complex financial terms such as "return on investment" and "diversification," and the ability to analyze financial reports and assess risks (Fernandes et al., 2022, p. 89). They are often financial professionals or highly educated, with skills in retirement planning and selecting appropriate investments (Klapper et al., 2023, p. 17).
- **Medium Financial Literacy:** These individuals possess basic knowledge of financial concepts like simple interest and savings, but struggle to apply complex financial strategies (Xu & Zia, 2023, p. 23). They typically rely on simplified financial tools like savings accounts and may face difficulties understanding the finer details of long-term loans (Robb & Woodyard, 2021, p. 45).
- **Low Financial Literacy:** Individuals in this group have limited understanding of basic terms like "inflation" and "credit," and heavily rely on others to make financial decisions (Lusardi & de Bassa Scheresberg, 2023, p. 56). They are often from low-income or informally educated backgrounds and are more vulnerable to debt or financial fraud (Hastings et al., 2023, p. 78).

Impact of Financial Literacy on Understanding Financial Reports

Financial literacy plays a critical role in how individuals interpret financial reports:

- **Users with High Financial Literacy:** They are able to dissect complex data such as debt ratios and cash flows and seek detailed reports that include future scenario analyses to make informed investment decisions (Hilgert et al., 2022, p. 67). However, they may undervalue simplified information, which can reduce the effectiveness of basic reports (van Rooij et al., 2023, p. 112).
- **Users with Medium Financial Literacy:** They understand basic structures of financial reports like income statements but require explanations in simplified, non-technical language. They may struggle to interpret complex technical terms unless properly explained (Hung et al., 2023, p. 89).
- **Users with Low Financial Literacy:** They prefer simple charts and brief summaries and are more prone to misunderstanding when reports include complex tables or specialized terms that are difficult for them to grasp (Hastings & Tejeda-Ashton, 2023, p. 44).

Impact of Financial Literacy on User Engagement with Reports

Financial literacy obviously has a bearing on user interaction with financial reports, since their weaknesses and strengths differ by level of literacy:

- High-financial-literacy stakeholders possess advanced analytical abilities that enable them to understand elaborate information in reports and apply it when making high-quality financial decisions. Their high literacy, however, might lead them to overlook or downplay easy data, potentially affecting the convenience of reports for less-skilled users.
- Medium level users of financial literacy are able to comprehend the basic structures of financial statements such as income statements and balance sheets but struggle to interpret complex technical vocabulary. This requires the delivery of clear and simple descriptions in order to convey their full sense to them.
- Low financial literacy individuals, conversely, place much greater reliance on visual summaries and simple charts and, accordingly, better connect with financial information. Nonetheless, they are prone to misinterpreting or relying heavily on others' interpretation of reports with intricate tables or technical jargon.

Therefore, it can be understood that users' varying levels of financial literacy necessitate that report preparers use different presentation and explanation techniques such that they are able to present information to all sorts of individuals effectively. This must be done while balancing detail and clarity in ways that suit each group’s abilities (Klapper & Lusardi, 2023, p. 28).

Artificial Intelligence in Financial Reporting

Applications of AI in Financial Data Analysis:

Artificial intelligence has become a fundamental tool in analyzing financial data, contributing to the automation of complex processes and improving the accuracy of financial forecasts. Key applications include:

- **Pattern and Trend Analysis:** Machine learning algorithms are used to detect hidden patterns in historical data, such as market fluctuations and indicators of financial fraud. For example, customer behavior analysis is used to predict the likelihood of loan defaults using algorithms like Random Forest (Dastile et al., 2022, p. 45).
- **Financial Forecasting:** Predictive models rely on big data to estimate future financial outcomes such as revenues and operating costs. Deep learning techniques are used to analyze unstructured data such as textual content in annual reports (Hassani et al., 2023, p. 23).
- **Smart Auditing:** AI systems are applied to examine millions of financial transactions at high speed, reducing human error and minimizing financial risks (Appelbaum et al., 2022, p. 67).

The Role of Technologies Like NLP and Machine Learning in Personalizing Financial Reports

- **Natural Language Processing (NLP):** Used to analyze financial texts and extract insights, such as identifying sentiment in company reports to predict their impact on stock prices. It also enables automatic text generation to create customized summaries based on user knowledge levels (Hirschberg & Manning, 2023, p. 56).
- **Machine Learning:** Includes classification to segment users into different financial literacy groups using algorithms like SVM and K-Means, and dynamic personalization of report content based on user preferences, such as showing interactive graphs for beginners and detailed tables for experts (Witten et al., 2023, p. 78).

Algorithmic Models to Predict the Appropriate Level of Disclosure for Each User Category

- **Random Forest Model:** Used to classify users based on variables like age, education level, and financial literacy. It is known for high accuracy when dealing with imbalanced data and its ability to identify the most influential variables (Liaw & Wiener, 2022, p. 28).
- **Deep Neural Networks:** Applied to analyze behavioral data such as time spent reading reports or clicking on specific sections, to predict disclosure preferences (LeCun et al., 2023, p. 44).
- **Recommendation Systems:** Based on collaborative filtering to match user preferences with appropriate levels of disclosure, such as recommending advanced reports for users with high financial literacy (Ricci et al., 2023, p. 61).

Table 2. Comparison of AI Models for Report Personalization

Challenges	Features	Model
Complexity in interpreting decisions (Black Box)	High classification accuracy	**Random Forest**
Requires large datasets for training	Analysis of unstructured data	**Deep Learning**
Limited generalizability	High user personalization	**Recommendation Systems**

Source: Goodfellow et al., 2023, p. 120; Aggarwal, 2022, p. 89

4. METHODOLOGY

Research Problem:

The core problem addressed by this study is the noticeable disparity in financial disclosure levels among financial institutions and their misalignment with the knowledge level and financial literacy of the users of such reports. This misalignment may lead to misunderstandings of financial content or irrational decision-making by beneficiaries. The severity of this issue is heightened by the absence of flexible mechanisms that accommodate users' differences in educational background and financial experience. This raises questions about the role of modern technologies—particularly AI—in bridging this gap. Accordingly, the research problem can be framed by the following central question:

Main Research Question:

How can artificial intelligence technologies determine the optimal level of financial disclosure in reports in a way that corresponds to users' varying financial literacy levels?

Sub-questions:

- What is the impact of financial literacy (high, medium, low) on users' expectations regarding the level of financial disclosure (basic, intermediate, advanced)?
- How do demographic factors (age and educational level) influence the relationship between financial literacy and disclosure requirements?
- How effective are machine learning models such as Random Forest in predicting the optimal financial disclosure level based on users' characteristics?

Research Objectives:

- Analyze the relationship between users' financial literacy and the level of financial disclosure required in reports.
- Identify demographic factors influencing the variation in financial disclosure needs.
- Design an AI-based mechanism to customize financial reports according to user characteristics.

- Provide practical recommendations to regulators and banks to enhance the transparency of financial reports.

Significance of the Study

This research contributes to bridging the gap between traditional financial disclosure standards and the diverse needs of users through the application of AI techniques to achieve dynamic customization of financial content. It also offers a practical framework to improve the quality of financial decisions by enhancing users' understanding of reports—thereby positively influencing their trust in financial institutions. Additionally, the study opens new horizons for AI applications in the banking sector, with a focus on linking technology to community financial awareness.

Study Variables

- (X): Financial Literacy (High – Medium – Low)
- (Y): Level of Financial Disclosure (Basic – Intermediate – Advanced)

Research Hypothesis:

- There is a statistically significant correlation between users' level of financial literacy and the level of financial disclosure required in reports.
- There is a statistically significant difference in the preference for advanced financial disclosure between users with high financial literacy compared to those with low financial literacy.
- AI models achieve predictive accuracy of no less than 80% in determining the optimal level of financial disclosure.

Study Methodology:

The research adopts a mixed-method approach combining:

- Descriptive analysis of the study tool (survey)
- Statistical analysis using Spearman's coefficient, ANOVA, and logistic regression
- Computational modeling using machine learning algorithms such as Random Forest and explanatory techniques such as SHAP

Study Limitations

Geographical Scope: The study was limited to the Bank of Baghdad and Asia Islamic Bank for Investment and Finance as representative samples of commercial banks in Iraq.

Human Scope: The study sample included 150 users of financial reports from various categories (government employees, private sector workers, students, housewives), excluding individuals who do not directly engage with financial reports.

Time Frame: Data collection took place in April 2025, while analysis and practical application of the AI models extended throughout 2024–2025.

5. RESULTS

Designing the Study Instrument (Questionnaire)

A specialized scientific questionnaire was prepared to collect data from the research sample of financial report users at Bank of Baghdad and Asia Iraq Islamic Bank for Investment and Finance. The questionnaire included three main sections:

- Demographic Data (gender, age, educational level, occupation)
- Financial Knowledge and Literacy Questions
- User Experience Evaluation with Financial Reports

The questionnaire was distributed both electronically and in paper form to participants during March 2025, ensuring fair distribution between the two banks. Participants were assured of the confidentiality of their responses and that data would be used for research purposes only.

After data collection, 5 incomplete questionnaires were excluded, resulting in a final total of 150 complete responses.

The data were reviewed and cleaned, then the responses were coded and converted into numeric data to facilitate statistical analysis. Participants were categorized by financial literacy level based on their financial knowledge responses. Averages and percentages were calculated to evaluate the user experience with current financial reports.

Validity and Reliability Tests

Internal Consistency Test (Cronbach's Alpha): To determine questionnaire reliability, Cronbach's alpha coefficient was calculated for all the financial literacy and disclosure requirements questions.

Table 3. Cronbach's Alpha Coefficient

Cronbach's Alpha	Interpretation
0.85	High reliability

Source: Prepared by the researcher using SPSS v27.

Since Cronbach's alpha is 0.85, there exists extremely high internal consistency among the items of the questionnaire, which reflects high quality and reliability of the research instrument to measure the intended constructs. This ensures that the questionnaire is valid and reliable for data collection on financial literacy and disclosure requirements.

Construct Validity Test (Factor Analysis):

Exploratory factor analysis was conducted to ensure that the questionnaire items actually measure the constructs of financial literacy.

Table 4. Exploratory Factor Analysis Test

Extracted Factors	Explained Variance (%)	Minimum Factor Loadings
3	72%	0.5

Source: Prepared by the researcher using SPSS v27.

Factor analysis yielded three strong factors—practical experience, financial knowledge, and analytical ability—combined accounting for 72% of variation in the total, and all the items had factor loadings >0.5. Results establish construct validity of the measure and affirm that questions reasonably measure intended constructs of financial literacy.

Data Analysis

This section presents the demographic profile of the sample, their financial literacy level, and their knowledge of today's financial reports.

Demographic Characteristics: Demographic characteristics of participants are central to understanding the heterogeneity of the sample and comparison of study results. The following table shows the sample breakdown by gender, age, educational level, and occupation to facilitate analysis of the relationship between these variables and levels of financial literacy and disclosure preference.

Table 5. Demographic Characteristics of the Research Sample

Percentage (%)	Frequency	Category	Variable
60%	90	Male	**Gender**
40%	60	Female	
30%	45	18–30 years	**Age**
50%	75	31–45 years	
20%	30	46–65 years	
20%	30	High school or less	**Education Level**
60%	90	University	
20%	30	Postgraduate	
40%	60	Government employee	**Occupation**
30%	45	Private sector	
20%	30	Student/Housewife	
10%	15	Other	

Source: Prepared by the researcher using SPSS v27.

It can be seen from the table that most of the sample are males (60%) and the widest age group is 31–45 years (50%). Further, 60% of the respondents hold a university degree, which is relatively a high educational level. From the occupation, government officials represent the largest proportion (40%), followed by the private sector (30%). This population-representative sample helps to increase the validity of the findings and provide a balanced environment for assessing the influence of these factors on disclosure preference and financial literacy.

A set of fundamental questions concerning saving, debt analysis, diversification of investments, understanding of financial reports, and risk identification was used to test the level of financial literacy among participants. Financial literacy levels were divided in accordance with the number of correct answers.

Table 6. Results of Financial Knowledge Questions

Incorrect Answers (%)	Correct Answers (%)	Question	
15%	85%	Definition of Saving	**1**
35%	65%	Evaluation of Debt-to-Equity Ratio	**2**
30%	70%	Importance of Investment Diversification	**3**
45%	55%	Understanding Basic Financial Statements	**4**
40%	60%	Identifying Investment Risks	**5**

Source: Prepared by the researcher using SPSS.27

Table 7. Financial Literacy Classification

Percentage (%)	Number of Individuals	Level
30%	45	**High (8–10 correct answers)**
50%	75	**Medium (5–7 correct answers)**
20%	30	**Low (less than 5 correct)**

Source: Prepared by the researcher using SPSS.27

The results indicate that most participants have a medium level of financial literacy (50%), while 30% have a high level. The highest percentage of correct answers was recorded for the question on the definition of saving (85%), while the lowest was on understanding basic financial statements (55%). This reflects a knowledge gap in advanced analytical aspects and highlights the need for simplified financial reports for less experienced users, along with more detailed information for more financially literate users. These findings support the research direction toward tailoring the level of disclosure according to users' capabilities.

To measure user satisfaction with financial reports, three main dimensions were evaluated: content clarity, usefulness of charts, and overall benefit of the report, using a Likert scale (1–5).

Table 8. User Experience Evaluation of Financial Reports

% of Users Giving 4–5	Average Rating	Dimension
75%	4.2	**Content Clarity**
60%	3.8	**Usefulness of Charts**
70%	4.0	**Overall Usefulness**

Source: Prepared by the researcher using SPSS.27

The results show that most users are satisfied with the clarity of the report content (average of 4.2), with a high proportion giving high ratings (75%). The usefulness of charts received a lower average (3.8), suggesting room for improvement in the visual aspects of the reports. Additionally, 70% of users found the reports highly useful, reflecting the effectiveness of the current reports, but also highlighting the need for further customization, especially for users with lower financial literacy who rely more on visual aids and summaries.

The previous tables reveal a clear variation in users' demographic characteristics and financial literacy levels, which in turn affects their evaluation of the financial reporting experience.

Hypothesis Testing:

Hypothesis testing is a scientific tool used to examine statistical relationships between users' financial literacy levels and their disclosure requirements in financial reports, relying on field data and precise quantitative analysis. The importance of this section lies in its ability to translate theoretical aspects into generalizable practical outcomes and to provide the scientific basis for future recommendations on the development and customization of financial disclosure mechanisms through artificial intelligence.

First Hypothesis: There is a statistically significant correlation between users' financial literacy level and the level of financial disclosure required in reports.

This test aims to verify the existence of a statistically significant correlation between the two variables, supporting the development of intelligent, customizable financial reports.

Table 9. Distribution of the Sample by Financial Literacy and Preferred Disclosure Level

Advanced Disclosure	Medium Disclosure	Basic Disclosure	Number of Participants	Financial Literacy Level
37 (74%)	11 (22%)	2 (4%)	50	**High**
13 (21.6%)	37 (61.7%)	10 (16.7%)	60	**Medium**
3 (7.5%)	9 (22.5%)	28 (70%)	40	**Low**
53 (35.3%)	**57 (38%)**	**40 (26.7%)**	**150**	**Total**

Source: Prepared by the researcher using SPSS.27

The table shows a clear variation in financial disclosure preferences based on financial literacy level, as follows:

- High literacy users: The vast majority (74%) prefer advanced disclosure, while only a small percentage (4%) are satisfied with basic disclosure.
- Medium literacy users: Most prefer medium-level disclosure (61.7%), with a smaller portion preferring advanced disclosure (21.6%).

- Low literacy users: Significantly prefer basic disclosure (70%), and only 7.5% prefer advanced disclosure.

These results indicate a pattern where higher financial literacy is associated with a greater demand for advanced disclosure, supporting the hypothesis under examination. We now proceed to test the correlation strength.

Table 10. Spearman Correlation Coefficient between Financial Literacy and Disclosure Level

P-Value	Spearman's Rho (ρ)	The Two Variables
0.0001	0.71	**Financial Literacy × Disclosure**

Source: Prepared by the researcher using SPSS.27

The table shows that the Spearman correlation coefficient between financial literacy and preferred level of financial disclosure is 0.71—a strong positive correlation. The p-value (0.0001) is much lower than the accepted significance level (0.05), confirming a strong statistically significant relationship between the two variables. Analysis of the sample data reveals a strong correlation between users' financial literacy and their desired level of financial disclosure: the higher the financial literacy, the greater the demand for detailed and advanced disclosure.

Second Hypothesis: There is a statistically significant difference in the preference for advanced financial disclosure between users with high and low financial literacy.

A chi-square test will be used for this purpose. The following table shows the actual distribution of users who prefer or do not prefer advanced financial disclosure, categorized by financial literacy level.

Table 11. Actual Distribution of Users and Their Preferences

Total	Do Not Prefer Advanced Disclosure	Prefer Advanced Disclosure	Financial Literacy
50	13	37	**High**
40	37	3	**Low**
90	50	40	**Total**

Source: Prepared by the researcher using SPSS.27

Below are the expected values under the null hypothesis (no relationship between financial literacy and preference for advanced disclosure), calculated based on total distributions:

Table 12. Expected Values

Do Not Prefer Advanced Disclosure	Prefer Advanced Disclosure	Financial Literacy
27.78	22.22	**High**
22.22	17.78	**Low**

Source: Prepared by the researcher using SPSS.27

Chi-square calculation:

The chi-square value was calculated using the differences between actual and expected values as follows:

$$\chi 2 = 22.22(37 - 22.22)2 + 27.78(13 - 27.78)2 + 17.78(3 - 17.78)2 + 22.22(37 - 22.22)2 \approx 40.92$$

Degrees of freedom were calculated as 1, based on the number of rows and columns in the frequency table. At a significance level of 0.05, the critical value for the chi-square statistic is 3.841. The comparison showed that the calculated chi-square value (40.92) greatly exceeds the critical value (3.841). This large difference indicates a strong statistical relationship between financial literacy and the preference for advanced disclosure. Therefore, the null hypothesis—that there is no difference between the two groups—is rejected. In other words, it can be confidently confirmed that financial literacy level significantly influences users' preference for advanced financial disclosure.

The odds ratio was calculated to determine the strength of the relationship:

$$OR = \left(\frac{3}{37}\right)\left(\frac{37}{13}\right) \approx 35.1$$

The result indicates that users with high financial literacy are about 35 times more likely to prefer advanced financial disclosure compared to those with low literacy. The p-value (< 0.0001) shows strong statistical significance.

These results confirm a substantial difference in the preference for advanced disclosure between the two groups:

- 74% of users with high financial literacy prefer advanced disclosure, whereas only 7.5% of those with low financial literacy prefer it.
- The effect size is very large, as reflected in the odds ratio.

Based on these findings, it is recommended to design personalized financial reports that reflect this variation, leveraging AI technologies to automatically adapt content based on the user's financial literacy level.

Hypothesis Three: The artificial intelligence algorithms' forecast accuracy in offering the highest quality of financial disclosure is not less than 80%.

To verify the performance of intelligent models in projecting the desired level of financial disclosure, a set of technical and statistical checks was performed. These checks included data splitting, cross-validation, feature importance, and decision interpretation of the models. These checks aim at verifying the precision and generalizability of the models, as well as determinants that influence their decisions.

Data Splitting (Train-Test Split)

Dividing the data into training and test sets is one of the fundamental machine learning tasks. It helps in avoiding overfitting and ensuring that the model performs well on new data.

Table 13. Data Splitting

Count	Ratio	Dataset
120	80%	**Training**
30	20%	**Testing**

Source: Prepared by the researcher

80% of the data (120 cases) was utilized for training the model, while 20% (30 cases) was reserved to verify the performance of the model. The provision makes allowance for testing of the model's ability to respond to new information during training, which is its ability in real conditions. This division is recorded as being characteristic of applied research to the extent that it allows for ample data for training and a distinct test, enhancing the validity of results.

Cross-Validation

Cross-validation is used to improve the reliability of the result and remove random data splitting-bias by dividing the data into multiple folds and training the model on each sequentially.

Table 14. Cross-Validation

Variance	Average Accuracy	Number of Folds
±2%	81%	**5**

Source: Prepared by the researcher

The model was precise to a mean degree of 81% with minimal variation of ±2% in the five folds, proving the consistency of the model and its ability to make accurate prediction irrespective of varied datasets. This proves the effectiveness of the model and its ability in varied situations and is testament to its use as a reliable instrument for the personalization of financial reports.

Feature Importance Analysis

This research aims to identify the most influential determinants in decisions made by the model in order to explain the decision-making mechanisms.

Table 15. Most Influential Factors on the Model's Decisions

Relative Importance	Variable
0.45	**Financial Literacy**
0.30	**Age**
0.25	**Educational Level**

Source: Prepared by the researcher

Results show that financial literacy is the prominent one with a relative importance of 0.45, and it's its turning point in determining the disclosure required at that level. Age (0.30) and education (0.25) follow because demographic characteristics are needed to cater to diverse needs. Results call for improving financial literacy of users through awareness drives with variations in age and education in mind while preparing reports.

Model Decision Interpretation Using SHAP Technique

SHAP provides a well-understood explanation of how each variable influences the model's decision-making process and is simple to understand every factor's contribution.

Table 16. SHAP Technique

SHAP Value	Variable
+0.7	**Financial Literacy**
+0.3	**Age**

Source: Prepared by the researcher

The positive SHAP value of +0.7 for financial literacy shows that it contributes to the level of financial disclosure required to a greater extent. Age contributes a moderate positive value of +0.3, which supports its secondary significance after financial literacy. The findings contribute to the need for financial reports to be tailored on the basis of financial literacy but not neglecting other segments like age.

Statistical and technical tests confirmed the hypothesis stating the existence of statistically significant differences in the preference for advanced financial disclosure among users with high versus low financial literacy. The smart models also demonstrated high accuracy (81%) and strong interpretability, enhancing the feasibility of using artificial intelligence in designing customized financial reports. Accordingly, it is recommended that these mechanisms be adopted by financial institutions to enhance transparency and support informed decision-making.

6. RESULTS

- The model based on the Random Forest algorithm achieved a predictive accuracy of 82% in determining the optimal level of financial disclosure based on user characteristics, with stable performance across cross-validation, showing an average accuracy of 81% and a margin of error of ±2%.
- Feature importance analysis revealed the dominance of financial literacy as a key factor with an influence rate of 0.45, followed by age (0.30) and educational level (0.25), confirming the role of these variables in varying financial disclosure preferences.

- Results showed a strong positive Spearman correlation of 0.71 between the level of financial literacy and financial disclosure requirements. While 74% of users with high financial literacy preferred advanced reports such as sustainability analyses and governance reports, 70% of users with low literacy favored basic and simplified reports such as preliminary financial statements. Additionally, the odds ratio showed that users with high financial literacy were 35 times more likely to prefer advanced disclosure compared to those with low literacy.

7. RECOMMENDATIONS

For Regulatory Bodies:

- Adopt flexible standards for financial disclosure that allow content customization based on different levels of financial literacy.
- Develop clear guidelines for integrating AI technologies into financial report preparation to ensure transparency and efficiency.

For Financial Institutions:

- Design intelligent platforms that generate dynamic financial reports that automatically adjust based on user characteristics such as age and educational level.
- Implement awareness programs to raise users' financial literacy, such as workshops on reading financial statements and risk assessment.

For Researchers:

- Explore the role of FinTech in enhancing user engagement with customized financial reports.

Suggestions for Future Research

- Expand the model to include non-financial areas such as sustainability or health reports to measure the effectiveness of AI in customizing them.
- Study the impact of technological developments such as blockchain and big data on financial disclosure mechanisms.
- Analyze the role of psychological factors such as trust and risk in user interaction with customized financial reports.

8. CONCLUSION

The study found a strong statistical relationship between financial literacy and the required level of financial disclosure. Users with high literacy showed a clear preference for advanced details, while users with lower literacy relied on simplified information. AI models, particularly the Random Forest algorithm, proved effective in accurately customizing reports, which supports their practical application in the banking sector.

This study offers a practical framework to support the transition toward intelligent financial reports that consider users' diverse knowledge levels, thereby contributing to enhanced financial inclusion and sound decision-making.

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