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# Artificial Intelligence Adoption in Financial Reporting: Evidence from a Technology Acceptance Model among Islamic Higher Education Students

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**A B S T R A C T**

The adoption of artificial intelligence in financial reporting is increasingly important as accounting practices move toward automation, data-driven analysis, and digital decision-making. This study aims to analyze the factors influencing users' intention to adopt artificial intelligence in financial reporting using the Technology Acceptance Model. A quantitative explanatory approach was applied, involving 93 students from state Islamic higher education institutions with academic experience in accounting, finance, financial reporting, or digital technology. Data were collected through a structured questionnaire using a five-point Likert scale and analyzed with Partial Least Squares Structural Equation Modeling. The measurement model showed adequate reliability and convergent validity, although the cross-loading results indicated potential conceptual overlap among several constructs. The structural model revealed that perceived ease of use had a positive and significant effect on attitude toward using and behavioral intention to use artificial intelligence. Perceived usefulness positively affected attitude but had a negative and significant effect on behavioral intention. Meanwhile, attitude toward using did not significantly affect behavioral intention and did not mediate the relationship between perceived usefulness, perceived ease of use, and intention to use artificial intelligence. These findings indicate that AI adoption in financial reporting is shaped more by direct perceptions of ease and practical usefulness than by user attitude alone. The study implies the need to strengthen AI literacy, technical readiness, and ethical awareness in financial reporting practices.

**KATA KUNCI**

Kecerdasan Buatan, Niat Menggunakan, Pelaporan Keuangan, Persepsi Kemudahan Penggunaan, Persepsi Kegunaan

**A B S T R A K**

Adopsi kecerdasan buatan dalam pelaporan keuangan semakin penting seiring berkembangnya praktik akuntansi berbasis otomasi, analisis data, dan pengambilan keputusan digital. Penelitian ini bertujuan untuk menganalisis faktor-faktor yang memengaruhi niat pengguna dalam mengadopsi kecerdasan buatan pada pelaporan keuangan menggunakan *Technology Acceptance Model*. Penelitian ini menggunakan pendekatan kuantitatif eksplanatori dengan melibatkan 93 mahasiswa perguruan tinggi keagamaan Islam negeri yang memiliki pengalaman akademik dalam akuntansi, keuangan, pelaporan keuangan, atau teknologi digital. Data dikumpulkan melalui kuesioner terstruktur dengan skala Likert lima poin dan dianalisis menggunakan *Partial Least Squares Structural Equation Modeling*. Hasil model pengukuran menunjukkan reliabilitas dan validitas konvergen yang memadai, meskipun hasil *cross-loading* mengindikasikan potensi tumpang tindih konseptual pada beberapa konstruk. Hasil model struktural menunjukkan bahwa persepsi kemudahan penggunaan berpengaruh positif dan signifikan terhadap sikap pengguna serta niat menggunakan kecerdasan buatan. Persepsi kegunaan berpengaruh positif terhadap sikap, tetapi berpengaruh negatif dan signifikan terhadap niat penggunaan. Sementara itu, sikap pengguna tidak berpengaruh signifikan terhadap niat penggunaan dan tidak memediasi hubungan antara persepsi kegunaan, persepsi kemudahan penggunaan, dan niat menggunakan kecerdasan buatan. Temuan ini menunjukkan bahwa adopsi kecerdasan buatan dalam pelaporan keuangan lebih ditentukan oleh persepsi langsung terhadap kemudahan dan manfaat praktis daripada oleh sikap pengguna semata. Implikasi penelitian ini menegaskan pentingnya penguatan literasi AI, kesiapan teknis, serta kesadaran etis dalam praktik pelaporan keuangan.

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## 1. Introduction

The development of artificial intelligence has transformed accounting and financial reporting practices by automating processes, improving efficiency, and enabling faster, more accurate processing of financial information. However, the use of artificial intelligence in accounting is not yet optimal because its acceptance is still influenced by technological readiness, perceived usefulness, ease of use, and users' ability to integrate technology into professional work processes [1], [2]. In the context of financial reporting, the issue is becoming increasingly important because the successful adoption of artificial intelligence has to do not only with the sophistication of the system, but also with the suitability of the technology for job needs, user trust, data security, audit efficiency, and the accuracy of the financial information generated [3], [4]. Therefore, this research needs to be conducted to examine the factors that affect the acceptance of artificial intelligence in financial reporting, particularly perceptions of usefulness, ease of use, job relevance, trust, security, and user readiness.

Several previous studies have shown that acceptance of artificial intelligence and digital technologies in accounting is influenced by perceived usefulness, ease of use, relevance to work, and user behavioral intentions [5], [6]. In the context of financial technology adoption, trust, security, and user readiness have proven to be important factors shaping the intention to use digital technology in financial activities and business administration [7], [8]. Other studies also confirm that blockchain technology has the potential to improve transparency, transaction traceability, the quality of accounting information, and the efficiency of financial and tax reporting systems [9], [10]. In addition, digital readiness and the adoption of integrated reporting systems are important factors in strengthening information quality, company value, and data-driven decision-making by stakeholders [11], [12]. Based on these findings, research on the adoption of artificial intelligence technology in financial reporting still has room for development, particularly in testing how the Technology Acceptance Model explains acceptance of AI to produce more accurate, efficient, transparent, and informative financial reporting.

Although the adoption of digital technologies in accounting has been widely studied in the context of fintech, blockchain, digital tax administration, and integrated reporting, research that specifically positions artificial intelligence as a key technology in financial reporting remains limited. Previous studies have shed more light on the acceptance of digital technology in general but have not specifically examined how users' perceptions of usefulness, ease of use, job relevance, trust, security, and readiness shape their intent to use AI in financial reporting. This gap is important because the success of AI implementation depends not only on the sophistication of the system but also on the acceptance by users directly involved in compiling and presenting financial statements. Therefore, this study aims to analyze the adoption of artificial intelligence technology in financial reporting using the Technology Acceptance Model as an analytical framework.

This research contributes to the development of digital accounting studies by positioning artificial intelligence as the primary focus in financial reporting, rather than merely as part of broader technology transformation. Theoretically, this study extends the Technology Acceptance Model to AI-based financial reporting by emphasizing the roles of perceived usefulness, ease of use, job relevance, trust, security, and user readiness. Empirically, this study provides evidence on the factors that shape the intention to use AI in financial reporting practices. In practical terms, the results of this research can serve as a basis for organizations, accountants, and policymakers in designing AI implementation strategies that are oriented not only to system sophistication but also to user readiness and acceptance.

## 2. Research Method

### 2.1. Research Design

This study uses a quantitative approach with an explanatory survey design to examine the factors influencing the adoption of artificial intelligence technology in financial reporting. This design was chosen because the research aims to test hypotheses, explain the predictive relationships between variables, and measure research constructs through statistically analyzed questionnaire instruments [13], [14]. The research model was tested using a structural analysis approach because the constructs were latent, measured with several indicators, and therefore analyzed by modeling the relationships among variables based on survey data [15], [16].

### 2.2. Population and Sample

The research population is students of state Islamic religious universities who are studying Islamic economics and finance. The research sample comprised 93 respondents, selected through non-probability purposive sampling, identified based on criteria aligned with the research objectives [14], [17]. The respondent criteria include being active students in at least the fourth semester and having gained academic experience in accounting, finance, financial reporting, or digital technology. This criterion is used so that respondents have an adequate basic understanding in assessing the potential use of AI in the process of compiling, analyzing, and presenting financial statements, as purposive sampling allows researchers to select participants based on characteristics relevant to the needs of research data [18]

### 2.3. Research Models and Variables

This study examines four main constructs, namely perceived usefulness (X1), perceived ease of use (X2), user attitude toward using (Z), and behavioral intention to use (Y). The four constructs are operationalized as a set of measurable indicators, which can be assessed using questionnaires and analyzed quantitatively [14], [19]. The perception of usefulness refers to the respondents' belief that AI can improve the efficiency, accuracy, speed, and quality of financial reporting. In contrast, the perception of ease of use refers to the respondents' belief that AI is easy to learn, understand, and use in financial reporting activities. User attitudes reflect respondents' positive assessments of AI use, while AI intentions indicate respondents' tendency to use AI in future financial reporting practices. The formulation of such constructs and indicators is undertaken to ensure that each latent variable has a clear, reliable, and appropriate measurement basis for testing structural models based on survey data [15], [20].

Table 1. Variable Operations

| Variable | Operational Definition | Key Indicators |
|---|---|---|
| Perceived Usefulness (X1) | Respondents' belief that AI provides benefits in financial reporting. | Improve reporting efficiency; improve data accuracy; accelerate report analysis; support the quality of financial information. |
| Perceived Ease of Use (X2) | Respondents' belief that AI is easy to learn and use. | Respondents' belief that AI is easy to learn and use. |
| Attitude Toward Using (Z) | Respondents' positive evaluation of the use of AI in financial reporting. | The use of AI is considered good; AI is considered relevant; respondents feel positive about AI; AI supports accounting and financial activities. |
| Behavioral Intention to Use (Y) | Respondents' propensity to use AI in financial reporting. | Desire to use AI; willingness to leverage AI; the tendency to recommend AI; commitment to learning AI for financial reporting. |

### 2.4. Instruments and Data Collection

Data were collected using a structured questionnaire with a five-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree. The instrument was developed by translating the research constructs into measurable questionnaire items, ensuring that each item reflected the intended variable and could capture respondents' perceptions, attitudes, and behavioral intentions consistently [21], [22]. Each item was adapted to the context of financial reporting to measure respondents' perceptions of usefulness, ease of use, attitude toward, and intention to use AI. Before analysis, the responses were screened to ensure completeness, conformity with respondent criteria, and feasibility for quantitative data analysis.

### 2.5. Data Analysis Techniques

The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS, as this technique is suitable for predictive research, can test direct and indirect relationships between latent variables, and can be applied to relatively small sample sizes. The analysis is carried out in two stages: the evaluation of the measurement model and the evaluation of the structural model. Evaluation of the measurement model includes testing outer loadings, Cronbach's alpha, composite reliability, average variance extracted (AVE), and discriminant validity to ensure that indicators and constructs meet validity and reliability criteria. The evaluation of the structural model was conducted by assessing the variance inflation factor (VIF), R-square, path coefficients, t-statistics, p-values, effect sizes, and mediation effects, using a bootstrapping procedure to test the significance of the relationships in the research model [23], [24].

### 2.6. Research Ethics

This study adheres to ethical principles by maintaining the confidentiality of respondents' identities, using data solely for academic purposes, and ensuring that participation is voluntary. Respondents were not asked to include personal information that could directly identify them. All data are analyzed in aggregate so that the results of the study do not identify any specific individual, but are used to explain the pattern of acceptance of AI in financial reporting.

## 3. Result and Discussion

### 3.1. Evaluation of Measurement Models

The measurement model is evaluated to ensure that the maintained indicators can represent the research construct. After the improvement of the indicator, all indicators used have an outer loading value above 0.70. This indicates that the indicator meets the criteria of convergent validity and is suitable for use in advanced testing. The result can be seen on Table 2 and Figure 1.

Table 2. External loading value of the maintained indicator

| Construct | Indicator | Outer loading |
|---|---|---|
| Perception of usefulness (X1) | X1.2 | 0.942 |
| Perception of usefulness (X1) | X1.4 | 0.865 |
| Perception of usefulness (X1) | X1.5 | 0.911 |
| Perception of ease of use (X2) | X2.2 | 0.749 |
| Perception of ease of use (X2) | X2.3 | 0.704 |
| Perception of ease of use (X2) | X2.4 | 0.812 |
| Perception of ease of use (X2) | X2.5 | 0.811 |
| Intention to use AI (Y) | Y.1 | 0.808 |
| Intention to use AI (Y) | Y.3 | 0.933 |
| User attitude (Z) | Z.1 | 0.873 |
| User attitude (Z) | Z.3 | 0.764 |
| User attitude (Z) | Z.4 | 0.906 |

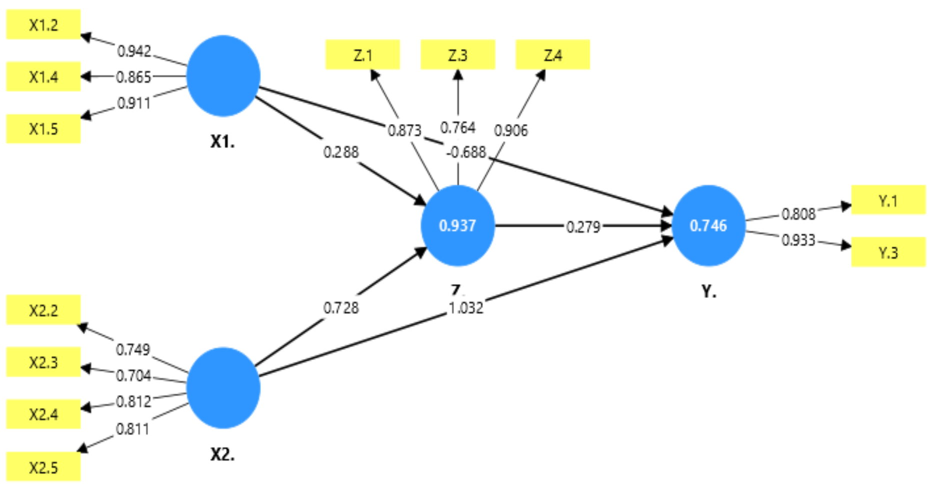


Figure 1. PLS-SEM End Model

The results of convergent reliability and validity on Table 3 show that the entire construct meets the recommended criteria. Cronbach's alpha value is in the range of 0.703 to 0.892, composite reliability is in the range of 0.853 to 0.932, and the Average Variance Extracted (AVE) of the entire construct is above 0.50. Thus, the research construct has adequate internal consistency and convergent validity.

Table 3. Construct Reliability and Convergent Validity

| Construct | Cronbach's alpha | rho_A | Composite reliability | AVE |
|---|---|---|---|---|
| X1 | 0.892 | 0.917 | 0.932 | 0.822 |
| X2 | 0.775 | 0.788 | 0.853 | 0.593 |
| Y | 0.703 | 0.823 | 0.864 | 0.762 |
| Z | 0.807 | 0.805 | 0.886 | 0.722 |

Although the reliability and validity of the convergent have been met, the results of cross-loading on Table 4 suggest that the validity of the discriminant needs to be examined further. Some indicators have a higher load on other constructs than on the original construct. For example, indicators X2.2 and X2.3 have higher loading at X1 than X2. In comparison, indicator Z.3 has a higher loading on Y than on Z. This suggests a potential overlap in meaning between indicators and warrants attention in the improvement of research instruments.

Table 4. Value Cross-Loading

| Indicator | X1 | X2 | Y | Z |
|---|---|---|---|---|
| X1.2 | 0.942 | 0.769 | 0.361 | 0.894 |
| X1.4 | 0.865 | 0.609 | 0.289 | 0.665 |
| X1.5 | 0.911 | 0.695 | 0.267 | 0.717 |
| X2.2 | 0.923 | 0.749 | 0.311 | 0.802 |
| X2.3 | 0.842 | 0.704 | 0.285 | 0.772 |
| X2.4 | 0.331 | 0.812 | 0.785 | 0.683 |
| X2.5 | 0.421 | 0.811 | 0.854 | 0.712 |
| Y.1 | 0.152 | 0.453 | 0.808 | 0.394 |
| Y.3 | 0.394 | 0.819 | 0.933 | 0.723 |
| Z.1 | 0.884 | 0.771 | 0.349 | 0.873 |
| Z.3 | 0.394 | 0.841 | 0.897 | 0.764 |
| Z.4 | 0.938 | 0.776 | 0.379 | 0.906 |

### 3.2. Structural Model Evaluation

The structural model is evaluated through R-square values, path coefficients, indirect influences, and effect size. Based on Table 5, the R-square value for the intent to use AI (Y) is 0.746. This means that the perception of usefulness can explain 74.6% of the variation in intentions to use AI, perceived ease of use, and users' attitudes. The R-square value for user attitude (Z) is 0.937, which means that 93.7% of the variation in user attitude can be explained by the perception of usefulness and the perception of ease of use. Both values indicate the model's strong predictive capabilities.

Table 5. R-square Value

| Construct endogenous | R-square | Interpretation |
|---|---|---|
| Intention to use AI (Y) | 0.746 | Strong |
| User attitude (Z) | 0.937 | Strong |

The results of the direct influence test on Table 6 showed that the perception of ease of use had a positive and significant effect on the intention to use AI ($\beta = 1.032$; $t = 3.687$; $p < 0.001$) and user attitude ($\beta = 0.728$; $t = 14.770$; $p < 0.001$). Perception of usefulness also had a positive and significant effect on user attitudes ($\beta = 0.288$; $t = 5.007$; $p < 0.001$). However, the direct effect of the perception of usefulness on the intention to use AI showed a negative and significant direction ($\beta = -0.688$; $t = 4.886$; $p < 0.001$). These findings need to be read carefully because they can be influenced by overlapping constructs, correlations between predictor variables, or the characteristics of respondents' answers. Meanwhile, user attitudes had no significant effect on intent to use AI ($\beta = 0.279$; $t = 0.801$; $p = 0.425$).

Table 6. Direct Impact Results

| Path | O | M | STDEV | t-statistic | p-value | Verdict |
|---|---|---|---|---|---|---|
| X1 → Y | -0.688 | -0.691 | 0.141 | 4.886 | 0.000 | Supported, negative direction |
| X1 → Z | 0.288 | 0.284 | 0.058 | 5.007 | 0.000 | Supported |
| X2 → Y | 1.032 | 1.094 | 0.280 | 3.687 | 0.000 | Supported |
| X2 → Z | 0.728 | 0.735 | 0.049 | 14.770 | 0.000 | Supported |
| Z → Y | 0.279 | 0.220 | 0.348 | 0.801 | 0.425 | Not supported |

The results of the mediation test on Table 7 showed that user attitudes did not mediate the relationship between perception of usefulness and intention to use AI ($\beta$ = 0.080; t = 0.795; p = 0.428). Consumer attitudes also did not mediate the relationship between perception of ease of use and intention to use AI ($\beta$ = 0.203; t = 0.780; p = 0.438). Thus, the influence of the perception of usefulness and the perception of ease of use on the intention to use AI does not run through user attitudes, but is more likely to be through direct consideration of the benefits and convenience of the system.

Table 7. Specific Indirect Influence Results

| Path | O | M | STDEV | t-statistic | p-value | Verdict |
|---|---|---|---|---|---|---|
| X1 → Z → Y | 0.080 | 0.069 | 0.101 | 0.795 | 0.428 | Not supported |
| X2 → Z → Y | 0.203 | 0.156 | 0.261 | 0.780 | 0.438 | Not supported |

The f-square value on Table 8 shows that the perception of usefulness has a major influence on the intention to use AI ($f^2$ = 0.497) and the user's attitude ($f^2$ = 0.537). The perception of ease of use has a moderate to large influence on the intention to use AI ($f^2$ = 0.388) and a very large influence on user attitudes ($f^2$ = 3.428). In contrast, user attitudes have very little influence on the intention to use AI ($f^2$ = 0.019). These results reinforce the finding that attitude constructs are not the main determinants of intention to use AI in this research model.

Table 8. Effect Size Results

| Relationship | f-square | Interpretation |
|---|---|---|
| X1 → Y | 0.497 | Large |
| X1 → Z | 0.537 | Large |
| X2 → Y | 0.388 | Heading big |
| X2 → Z | 3.428 | Very large |
| Z → Y | 0.019 | Very small |

## 3.3. Discussion

The results of the evaluation of the measurement model showed that the maintained indicators had met the convergent validity because the entire outer loading value was above 0.70, while the values of Cronbach's alpha, composite reliability, and AVE also showed adequate reliability and convergent validity in each study construct [25], [26]. However, the cross-loading results indicate a potential problem with discriminant validity, as some indicators load higher on other constructs than on their original constructs. Hence, the conceptual separation among perceptions of usefulness and ease of use, user attitude, and intention to use AI still needs careful examination [27], [28].

The results of the structural model test showed that the perception of ease of use had a positive and significant effect on the intention to use AI and user attitudes, which confirmed that ease of operation is an important factor in driving the adoption of AI, especially when users judge that the technology does not add to the technical and cognitive burden in the learning process, accounting, and financial reporting [2], [29]. These findings also reinforce the view that the adoption of AI in the field of accounting and auditing depends not only on technological sophistication, but also on the readiness of digital competencies, perception of use, and the ability of users to integrate AI into professional and academic activities [30], [31].

The negative influence of usefulness perception on the intention to use AI needs to be read critically, as such results may indicate an overlap of constructs, a depressing effect between predictor variables, or the ambivalence of respondents who recognize the benefits of AI but are not yet fully convinced to use it in the context of financial reporting [32], [33]. The insignificance of the influence of user attitudes on the intention to use AI and the unproven role of attitude mediation show that the intention to use AI in this study is more determined by direct considerations of convenience, practical benefits, trust, ethics, subjective norms, and context of use than by the evaluative attitude of users alone [34], [35].

The novelty of this research lies in testing the AI acceptance model in the context of financial reporting by using the constructs of usefulness perception, ease of use perception, user attitude, and intention to use AI. This study not only shows the relationships among variables in the TAM model, but also presents the critical finding that perceived usefulness hinders the intention to use AI. User attitude does not serve as a mediator. The findings suggest that the adoption of AI in financial reporting does not necessarily follow the linear pattern of the classic technology acceptance model. Users can recognize the benefits of AI, but they may not necessarily have a strong intention to use it if there are still doubts, overlapping perceptions, or unpreparedness in practically understanding the functions of AI.

The theoretical implications of this study suggest that AI acceptance models need to be developed more contextually, especially in the field of financial reporting, which demands accuracy, prudence, and users' evaluative ability. The results of this study show that the intention to use AI is more influenced by direct considerations of the convenience and practical benefits of the system than by the attitude of the user. The practical implication is that educational institutions, accounting study programs, and financial institutions need to strengthen AI literacy, technical training, and ethical understanding in the use of AI. This strengthening is important so that users not only view AI as a useful technology but also use it appropriately, critically, and responsibly in the financial reporting process.

The limitations of this study lie in the relatively limited number of respondents, the cross-sectional design of the study, and the indication of overlapping constructs in the cross-loading results. This condition means that generalizing findings still requires careful consideration, especially since the context of AI acceptance can vary with the user's background, technological experience, and academic or professional environment. Further research is recommended to involve larger sample counts, use more specific instruments, and test the validity of the discriminant with additional approaches such as HTMT. The next research can also include other variables such as trust, risk, ethics, subjective norms, technological readiness, and digital competence so that the adoption model of AI in financial reporting can be explained more comprehensively.

## 4. Conclusion

The adoption of artificial intelligence in financial reporting is mainly determined by users' direct perceptions of ease of use and practical usefulness rather than by attitude alone. The measurement model indicates adequate reliability and convergent validity. However, the cross-loading results indicate that several indicators still require refinement due to conceptual overlap among perceived usefulness, perceived ease of use, attitude toward using, and behavioral intention. The structural model confirms that perceived ease of use has a positive and significant effect on both attitude and intention to use AI. In contrast, perceived usefulness positively influences attitude but negatively affects behavioral intention. Attitude toward using AI does not significantly influence behavioral intention and does not mediate the relationship between perceived usefulness, perceived ease of use, and intention to use AI. These findings show that AI acceptance in financial reporting does not fully follow the linear assumptions of the classical Technology Acceptance Model. Users may recognize the benefits of AI, but their intention to use it depends more strongly on whether the technology is perceived as easy, practical, and applicable to financial reporting tasks. Theoretically, this study implies that AI acceptance models in accounting and financial reporting need to include contextual factors such as user readiness, trust, risk, ethics, and digital competence. Practically, educational institutions, accounting programs, and financial organizations should strengthen AI literacy, technical training, and ethical awareness so that users are prepared to apply AI critically, accurately, and responsibly in financial reporting practices.

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