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Artificial Intelligence Ethics Best Practices Model for Financial Decision-Making in Chinese Financial Institutions

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ABSTRACT

Chinese financial institutions (CFIs) are increasingly embracing artificial intelligence (AI) for their financial decision-making driven by AI's capacity to mitigate risks and enhance efficiency and accuracy. However, there remain ethical challenges related to the integration of AI in financial decision-making. This study develops the AI ethics best practices model (AB-PraM) to mitigate ethical concerns and enhance the application of AI in financial decision-making. By employing a quantitative methodology, this research collected questionnaire data from 320 financial experts in CFIs. Structural equation modelling (SEM) was adopted to identify AI ethics best practices for the implementation of the AB-PraM. The findings of this research will mitigate AI ethics challenges in CFIs and provide a practical framework for transparent and accountable decision-making in alignment with ethical standards and regulations.

KEYWORDS

Artificial Intelligence, Chinese Financial Institutions, Ethics Best Practices, Financial Decision-Making

INTRODUCTION

In recent years, artificial intelligence (AI) technologies have demonstrated exceptional capabilities in intelligent tasks, such as problem-solving, pattern recognition, and decision-making (Marda, 2018; Mogaji & Nguyen, 2022). Since recognizing this potential, financial service providers have increasingly incorporated AI into their operations to enhance the accuracy of financial decisions (Truby et al., 2020). The use of AI algorithms, capable of vast dataset analysis and intricate pattern recognition, not only streamlines operational processes but also delivers personalized financial services to ensure customer satisfaction (Northey et al., 2022). Moreover, AI's rapid fraud detection capabilities play a crucial role in protecting institutions and clients from financial losses and security breaches (Ghazwani et al., 2022).

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China, a global financial powerhouse, demonstrates a particularly pronounced commitment to AI adoption. According to *China Daily*, Chinese financial institutions (CFIs) have invested over 56 billion yuan (approximately USD 7.6 billion) in AI-related hardware and software. The rapid implementation of AI technology by CFIs has given rise to new theoretical and managerial challenges (Bussmann et al., 2020). Ethical concerns, particularly regarding data collection, algorithmic biases, and discrimination, have surfaced as CFIs collect data to train and operate their AI systems (Jiang et al., 2020; Xie, 2019; Zhao, 2021). Roberts et al. (2021) have emphasized the need to identify and address ethical issues for responsible and effective AI utilization in financial institutions. However, there remains a critical theoretical gap, particularly in the identification and resolution of the ethical issues surrounding the use of AI in financial decision-making processes.

The unique cultural and regulatory environment of China's financial industry introduces distinct challenges and considerations that significantly influence the implementation of AI ethics best practices. In the context of deeply ingrained cultural conventions, CFIs are characterized by collective values, social harmony, and Confucian principles (Wen et al., 2021). These cultural factors may shape the perception of ethical considerations in AI adoption and influence the interpretation and prioritization of fairness and transparency. Additionally, the active role of the government in shaping the regulatory framework adds another layer of complexity (Lee, 2020). The regulatory environment plays a crucial role in defining the boundaries within which financial institutions operate, affecting the implementation of AI ethics best practices. For instance, compliance with government directives and regulations may influence the extent to which financial institutions can adopt certain AI technologies or the degree of transparency required in algorithmic decision-making. Thus, Chan et al. (2022) opined that ethical practices regarding AI need to be adaptable to these specific cultural and regulatory considerations to ensure their effectiveness and relevance in guiding responsible AI use in the Chinese financial context.

Building upon the recognition of cultural and regulatory factors in AI integration, studies have been conducted to enhance the integration of AI in financial decision-making. For instance, Fan et al. (2022) proposed an explainable AI model for application in fintech risk management. Roberts et al. (2021) analyzed the strategic areas in which China is investing in AI and the concurrent ethical debates delimiting its use. Boukherouaa et al. (2021) investigated the opportunities and risks associated with AI in finance, and Gigante and Zago (2023) conducted a comprehensive assessment of AI-based frameworks in the financial industry. Despite these efforts, a critical knowledge gap remains unaddressed concerning the identification and resolution of the ethical issues of AI utilization in financial decision-making processes. Mogaji et al. (2022) highlighted the persistent AI ethical challenges confronting financial service providers. In the Chinese context, Roberts et al. (2021) and Chan et al. (2022) emphasized the absence of a comprehensive and context-specific AI ethics framework tailored to the unique challenges and dynamics of the Chinese financial sector. The identified gap underscores the need for further research that develops practical best practices to address AI ethical challenges in the financial decision-making landscape.

Therefore, this research addresses this gap through the development of practical best practices to handle AI ethical challenges in financial decision-making within CFIs. The primary objective is to contribute valuable insights and applicable guidelines for the mitigation of AI-related ethical concerns in financial decision-making processes. The proposed AB-PraM is a framework that guides transparent and accountable decision-making. The research employs a quantitative methodology, including a questionnaire survey and structural equation modeling (SEM), to understand and identify the core factors influencing AI-driven decision-making.

The research is expected to make several contributions. Firstly, it explores the ethical implications associated with the integration of AI into financial decision-making processes to fill the outlined theoretical gap. Secondly, the research seeks to mitigate AI ethics challenges in financial decision-making processes and contribute to the broader discourse on the responsible use of AI in the financial sector. Thirdly, the study is specifically tailored for CFIs, as it considers their unique challenges and dynamics.

LITERATURE REVIEW

AI ethical issues in financial decision-making are multifaceted, encompassing moral concerns and societal implications regarding AI use in the financial industry. Central to these concerns are transparency, fairness, accountability, and potential biases in AI systems which influence decision-making processes and outcomes (Agarwal et al., 2021). Scholars have delved into the generic ethical challenges associated with AI-driven financial decision-making, and their findings are critically evaluated and summarized in Table 1 below which illustrates prevalent AI ethical challenges.

The literature suggests that algorithmic bias and unfairness in financial decision-making lead to discriminatory practices, inaccurate financial risk assessments, and legal and regulatory challenges

Table 1. Summary of AI ethical challenges in financial decision-making

No.	Ethical Challenges (EC) in AI-Driven Financial Decision-Making	Chan et al. (2022)	Mogaji et al. (2022)	Tzimas (2021)	Balasubramaniam et al., (2020)	Došilović et al. (2018)	Redrup Hill et al. (2023)	Guan, J. (2019)	Joseph (2020)	Lee (2020)	Northey et al. (2022)
AI_ EC1	Lack of Algorithmic Fairness		✓	✓	✓	✓		✓			✓
AI_ EC2	Inadequate Transparency	✓	✓		✓		✓	✓			
AI_ EC3	Privacy and Security Issues		✓	✓	✓	✓		✓	✓		✓
AI_ EC4	Data Quality Limitations	✓	✓		✓					✓	
AI_ EC5	Limited Explainability	✓				✓				✓	✓
AI_ EC6	Accountability Challenges		✓	✓		✓			✓		
AI_ EC7	Regulatory Compliance Hurdles	✓	✓	✓	✓		✓	✓	✓		✓
AI_ EC8	Insufficient Interpretability	✓		✓			✓	✓			
AI_ EC9	Bias Detection Challenges	✓	✓		✓	✓			✓		
AI_ EC10	Human Oversight Gaps	✓			✓		✓	✓		✓	
AI_ EC11	Ethical Leadership Issues	✓	✓	✓							✓
AI_ EC12	Stakeholder Engagement Challenges			✓		✓	✓			✓	
AI_ EC13	Data Governance Complexities	✓	✓			✓					✓
AI_ EC14	Risk Assessment Limitations		✓		✓	✓		✓			

(Balasubramaniam et al., 2020; Long et al., 2021). Biased decisions, as noted by Ghazwani et al. (2022), result in tangible consequences that negatively affect the financial performance of institutions, such as investment and trading losses. Moreover, ethical issues related to the lack of transparency and explainability in financial decision-making contribute to a decline in investor trust (Lui et al., 2018; Bussmann et al., 2020; Sheth et al., 2022). Truby (2020) emphasizes that this lack of trust is a primary catalyst for the transfer of loyal customers to competitors, which constitutes a grave threat to the credibility, customer base, revenue, profitability, and market share of an institution (Tzimas, 2021). Privacy concerns in financial decision-making, as highlighted by Mogaji et al. (2022), raise apprehensions regarding the collection, storage, and use of sensitive customer data, and the potential implications include breaches, legal consequences, and a loss of customer trust. Additionally, regulatory non-compliance, as posited by Cui (2022), can result in legal ramifications, financial losses, and reputational damage.

In summary, the literature underscores the intricate interplay of ethical challenges in AI-driven financial decision-making, emphasizing the need for robust measures to address algorithmic bias, lack of transparency, and privacy concerns. These efforts are crucial for sustained trust, credibility, and performance of financial institutions.

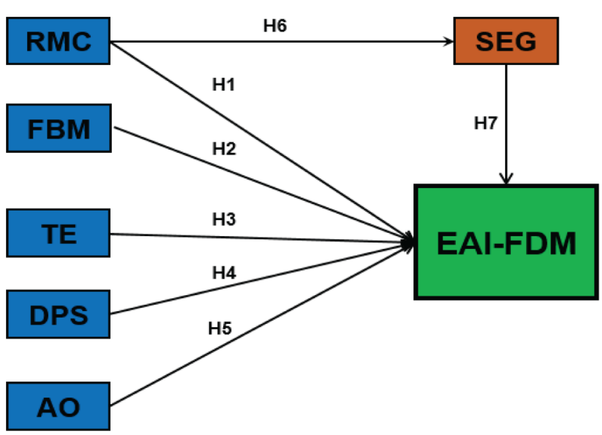
Conceptual Framework

In the context of this study, the conceptual framework outlines the critical AI ethics best practices to address the identified issues and enhance the use of AI in financial decision-making in the CFI context. The framework encompasses the generic AI ethics best practices henceforth referred to as variables . These variables are categorized into three groups, each represented by a different color. Category 1, the independent variables, include risk management and compliance (RMC), fairness and bias mitigation (FBM), transparency and explainability (TE), data privacy and security (DPS), and accountability and oversight (AO). Category 2, the mediating variable, comprises stakeholder engagement and governance (SEG). Category 3, the dependent variable, represents AI-driven financial decision making (EAI-FDM). The conceptual framework is shown in Figure 1.

Hypotheses Development

Practical tools and processes for risk assessment in AI-driven financial decisions, as emphasized by Bussmann et al. (2020), help financial institutions to identify and mitigate potential risks to enhance the accuracy and reliability of decision-making processes. Monitoring AI ethics compliance with evolving financial regulations and ethical standards in financial decision-making

Figure 1. Conceptual framework of AI ethical best practices for financial decision-making



ensures that financial institutions remain aligned with legal requirements and ethical best practices, reducing the risk of regulatory violations (Zheng et al., 2019; Chan et al., 2022; Charles et al., 2022). Hentzen et al. (2021) suggested that the evaluation of the potential risks associated with AI-driven financial decisions enables institutions to proactively address and minimize risks and improve the overall quality of their decision-making. With these considerations, the following hypothesis is developed:

H1: There is a positive significant relationship between risk management and compliance and AI-driven financial decision-making in Chinese financial institutions.

The use of metrics to quantify fairness in AI-driven financial decisions allows financial institutions to identify disparities in the treatment of different demographic groups (Ghazwani et al., 2022). This is a crucial step in potential bias remediation (Cui, 2022). Another key best practice, as identified by Hentzen et al. (2021), involves diverse data training to ensure fairness in financial outcomes. By assessing training data for representatives and diversity, institutions can identify and rectify the underrepresentation of certain groups to enhance fairness in AI-driven decisions (Ghazwani et al., 2022). Additionally, Bussmann et al. (2020) advocate for effective bias remediation to address biases upon detection, which provides a framework for continuous bias mitigation. With these considerations, the following hypothesis is developed:

H2: There is a positive significant relationship between fairness and bias mitigation and AI-driven financial decision-making in Chinese financial institutions.

According to Redrup et al. (2023) and Santosh and Wall (2022), comprehensive documentation of AI models is crucial for trust building, increased clarity, and greater transparency and explainability in AI-driven financial decision-making. To mitigate concerns about AI complexity and the need for clarity in financial decision-making within financial institutions, another essential approach is to measure AI model interpretability through metrics, as suggested by Tzimas (2021). Additionally, as guided by Santosh and Wall (2022), in response to the challenges related to the understandability of AI-generated outcomes, it is vital to assess stakeholders' comprehension of AI-driven financial decisions.

H3: There is a positive significant relationship between transparency and explainability and AI-driven financial decision-making in Chinese financial institutions.

Robust data privacy and security in AI-driven financial decision-making is imperative for trust building, regulatory compliance, and ethical AI implementation (Rowan et al., 2021). Bussmann et al. (2020) and Ghazwani et al. (2022) have advocated for tracking and assessing security incidents as a suitable best practice that enhances data protection and effectively safeguards sensitive financial data. Additionally, Cui (2022) highlights the importance of the evaluation of the data encryption method's effectiveness to maintain the confidentiality of financial information in AI-driven decision-making.

H4: There is a positive significant relationship between data privacy and security and AI-driven financial decision-making in Chinese financial institutions.

Accountability and oversight in AI-driven financial decision-making are essential for transparency, ethics, and responsible use of AI. This includes the definition of clear roles and responsibilities for those involved in AI decisions related to financial outcomes (Payne et al., 2021). This also consists of efficiency maintenance in the resolution of errors or ethical issues that may arise in AI-driven financial decisions (Boukherouaa et al., 2021; Zhang, 2021). Ghazwani et al. (2022) emphasize the importance of assessing the impact imposed by ethical leadership on accountability in financial decision-making, as ethical leadership sets the tone for responsible AI use. With these considerations, the following hypothesis is developed:

H5: There is a positive significant relationship between accountability and oversight and AI-driven financial decision-making in Chinese financial institutions.

SEG plays a mediating role in the enhancement of RMC and, consequently, AI-driven financial decision-making in financial institutions. The measurement of stakeholder involvement in AI-driven financial decision-making aligns RMC practices with the expectations and needs of stakeholders, which in turn enhances overall risk management effectiveness (Méndez-Suárez et al., 2019; Rajagopal et al., 2022; Duft et al., 2020). According to Dwivedi et al. (2021), stakeholders' feedback on AI decisions facilitates a continuous feedback loop and provides insights for financial institutions in their compliance with risk management measures.

Given that the identified ethics best practices are novel, more cohesive utilization is required to enhance AI-driven financial decision-making. However, these generic best practices may not be directly applicable in the context of CFI (Chan et al., 2022). In light of this, another key objective of this study is to conduct an empirical investigation to identify AI ethics best practices to address AI-driven decision-making issues specific to the context of CFI. These best practices will be incorporated into a model for cohesive applicability. With these considerations, the following hypotheses are developed:

H6: Stakeholder engagement and governance mediate the relationship between risk management and compliance and AI-driven financial decision-making in Chinese financial institutions.
H7: There is a positive significant relationship between stakeholder engagement and governance and AI-driven financial decision-making in Chinese financial institutions.

RESEARCH METHODOLOGY

This research employs a quantitative research approach to address the research objectives: (1) investigation into AI ethics challenges; (2) identification of the best practices for challenge mitigation; (3) the development of an AI-ethics best practices model for reliable and trusted financial decision-making, specifically for CFIs.

Questionnaire Design

The questionnaire in this research is divided into three sections. Section A was used to gather demographic information about the respondents. Section B involved an investigation into the critical AI ethical challenges in financial decision-making (refer to Table 1) on a Likert scale of 1–5: 1–Least Significant, 2–Moderately Significant, 3–Neutral, 4–Highly Significant, and 5–Extremely Significant. Section C identified the ethical AI best practices for financial decision-making on the five-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (5). The constructs were measured using the variables identified from the literature review (refer to Table 2).

Data Collection

The study targets financial experts within Chinese financial institutions, including risk management officers, financial analysts, senior investment bankers, hedge fund managers, tax directors, and other relevant roles. A stratified random sampling method is employed to ensure representation across these diverse roles, contributing to a comprehensive understanding of AI ethics challenges. Before finalizing the main questionnaire, a pilot survey was conducted to ensure validity and reliability, as

Table 2. Constructs of questionnaire

Ethical Best Practices for AI-Driven Financial Decision-Making in Chinese Financial Institutions		Sources
Fairness and Bias Mitigation (FBM)		
FBM1	Training data diversity and representatives to ensure fairness in financial outcomes.	Ghazwani et al. (2022); Cui (2022); Hentzen et al. (2021); Redrup et al., (2023).
FBM2	Providing tools for detecting bias in AI algorithms and quantifying bias in financial decisions.	
FBM3	Using metrics to measure fairness in AI-driven financial decision-making.	
FBM4	Effective bias remediation processes to rectify biased AI-driven financial decisions.	
FBM5	Implementation of a feedback mechanism for users to report potential biases or unfair decisions in financial contexts.	
Transparency and Explainability (TE)		
TE1	Ensuring thorough documentation of AI models, encompassing data sources, algorithms, and decision-making processes.	Redrup et al. (2023); Santosh and Wall (2022); Tzimas (2021).
TE2	Assessing how well stakeholders comprehend AI-driven financial decisions.	
TE3	Using metrics to measure the interpretability of AI models in financial decision-making.	
TE4	Measuring the effects of transparency-enhancing techniques such as visualizations or explanations on financial decision-making.	
TE5	Collecting user feedback to gauge the clarity and understandability of AI-driven financial decisions.	
Data Privacy and Security (DPS)		
DPS1	Tracking and assessing security incidents to enhance data protection in AI-driven financial decision-making.	Chan et al. (2022); Cui (2022); Mogaji and Nguyen (2021). .
DPS2	Evaluating data encryption methods' effectiveness in safeguarding sensitive financial data.	
DPS3	Assessing compliance audit results related to data privacy in the context of financial decisions.	
DPS4	Measuring response time to data security incidents in financial settings.	
DPS5	Gathering user feedback to gauge their perception of data protection in financial decision-making.	
Accountability and Oversight (AO)		
AO1	Clarifying roles and responsibilities for AI-driven financial decisions.	Payne et al. (2021); Boukherouaa et al. (2021); Ghazwani et al. (2022); Riedel et al. (2022).
AO2	Efficiency in resolving errors or ethical issues in AI decisions related to financial outcomes.	
AO3	Assessing ethical leadership's impact on accountability in financial decision-making.	
AO4	Collecting feedback from stakeholders about their satisfaction with accountability mechanisms in financial contexts.	
AO5	Monitoring the frequency and content of reports related to AI-related incidents or errors in financial decision-making.	
Risk Management and Compliance (RMC)		
RMC1	Monitoring compliance with evolving financial regulations and ethical standards in financial decision-making.	Mogaji and Nguyen (2021); Payne et al. (2021); Riedel et al. (2022); Redrup et al. (2023).
RMC2	Using effective tools and processes for risk assessment in AI-driven financial decisions.	
RMC3	Measuring the ability to adapt AI systems to new regulatory requirements in financial contexts.	
RMC4	Evaluating potential risks associated with AI-driven financial decisions.	
RMC5	Collecting feedback on stakeholder trust in compliance efforts and their perception of regulatory alignment in financial decision-making.	

continued on following page

Table 2. Continued

Ethical Best Practices for AI-Driven Financial Decision-Making in Chinese Financial Institutions		Sources
Stakeholder Engagement and Governance (SEG)		
SEG1	Ensuring stakeholder involvement in AI-driven financial decision-making.	Xivuri and Twinomurinzi (2021); Santosh and Wall (2022); Balasubramaniam et al. (2020).
SEG2	Evaluating communication about AI use in financial decisions.	
SEG3	Ensuring efficiency of governance structures overseeing AI decisions.	
SEG4	Establishing a system for stakeholders' feedback on AI decisions.	
SEG5	Ensuring understanding and adherence to ethical guidelines.	
Ethical AI-Driven Financial Decision Making (EA1-FDM)		
EAI-FDM1	Ethical AI-driven financial decision-making streamlines data processing, reducing operational costs and enabling faster decisions in Chinese financial institutions.	Santosh and Wall (2022); Tzimas (2021); Xivuri and Twinomurinzi (2021); Došilović et al. (2018).
EAI-FDM 2	Ethical AI models make precise predictions, reducing errors in financial decisions within Chinese financial institutions.	
EAI-FDM3	Ethical AI identifies and mitigates real-time risks, aiding compliance and investment decisions while adhering to ethical guidelines in Chinese financial institutions.	
EAI-FDM4	Ethical AI analyzes customer data for tailored financial offerings and improved satisfaction, aligning with ethical practices.	
EAI-FDM5	Ethical AI uncovers hidden patterns in financial data, informing strategic choices while adhering to ethical standards.	

recommended by Jin et al. (2023). Validation of a research instrument is crucial for study credibility (Almatari et al., 2023). The questionnaire conducts refinement with input from five randomly selected senior financial managers from Chinese financial institutions, which yielded a reduction in variables from 42 to 35. Specifically, repetitive and irrelevant items were deleted in accordance with prior studies such as Sekaran and Bougie (2019). Subsequently, the pilot survey was distributed to 30 financial professionals in Chinese financial institutions.

Cronbach's alpha was used to assess the internal consistency of the questionnaire to ensure reliable measurement of the variables of interest. Based on the results shown in Table 3, each main variable meets the 0.7 threshold (Jin et al., 2023), affirming the credibility and suitability of the questionnaire.

After the pilot survey, the main questionnaire was distributed to financial experts of different backgrounds across Chinese financial institutions. The research questionnaires were distributed to 1000 respondents who were selected based on recommendations, research output, and established networks through conferences, research and training groups, and research collaborations. 320 appropriately-answered questionnaires were received, with a 32% response rate, which is considered sufficient for research (Almatari et al., 2023). The detailed demographic analysis of the respondents is described in Figure 2.

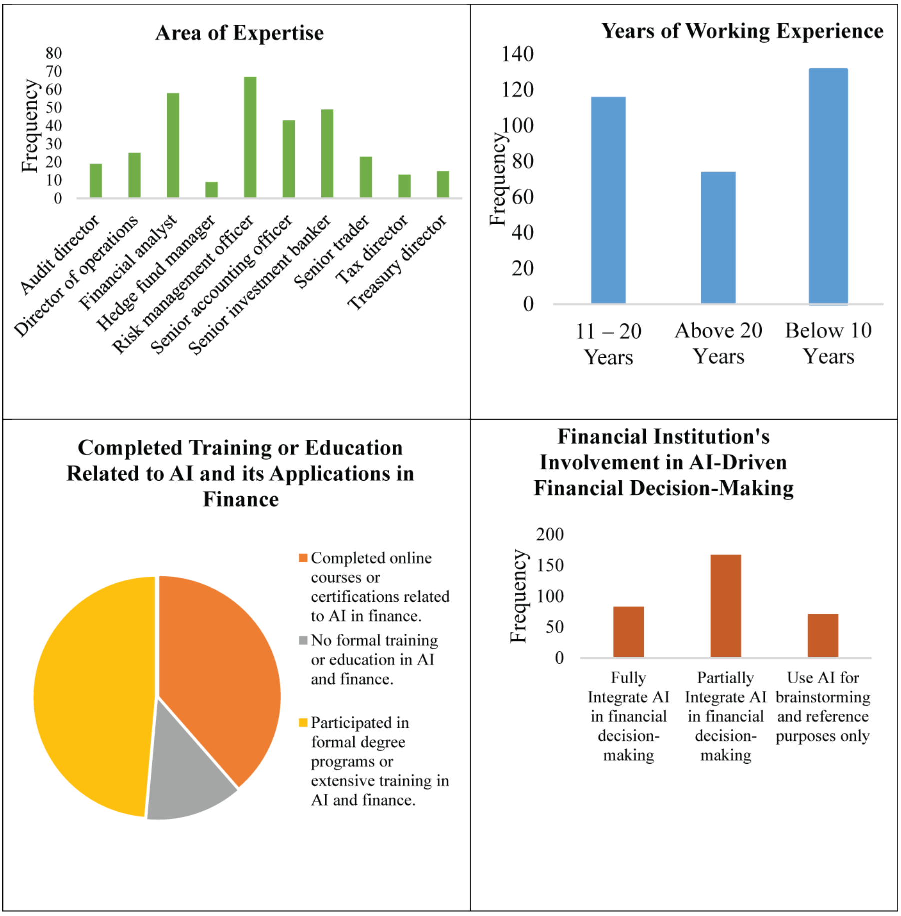
Descriptive Statistics and Relative Importance Index

Descriptive statistics were employed to analyze the demographics of the 320 respondents for insights into their current positions, years of working experience, the nature of their institutions'

Table 3. Results of variables reliability

	RMC	FBM	TE	DPS	AO	SEG	EAI-FDM
Cronbach's alpha	0.77	0.86	0.90	0.78	0.80	0.87	0.90
No. of Items	5	5	5	5	5	5	5

Figure 2. Demographic analysis of the respondents



involvement in AI-driven financial decision-making, and the types of AI-related training or financial education they received. This approach provides a comprehensive overview of the respondent group. This was followed by an investigation into the AI ethical challenges associated with financial decision-making in Chinese Financial Institutions and the utilization of descriptive statistics, particularly the measures of central tendency, the mean, and measures of dispersion, the standard deviation, for data analysis. According to Sekaran and Bougie (2019), both mean and standard deviation can be used for quantitative data analysis to reveal data variability and ensure distribution spread.

Relative Importance Index (RII) was used to quantitatively assess the relative significance of various AI ethical challenges (Sekaran and Bougie, 2019). By ranking these factors, RII aids in effort prioritization, resource allocation optimization, and informed decision-making. The formula in Equation 1 was used to calculate RII:

$$\mathrm{RII} = \frac{\sum(Wi\,x\,Xi)}{Nx5} \tag{1}$$

Structural Equation Modelling

The research framework employed structural equation modeling through a five-step process to ensure systematic and rigorous analysis. Step 1 specified the model, including relationships, paths, and hypotheses. Confirmatory factor analysis (CFA) in the analysis of moment structure (AMOS) validated indicators representing constructs, as recommended by Gunduz and Elsherbeny (2020). Step 2 involved model specification to guarantee estimable results. In Step 3, model estimation minimized differences between theoretical and observed covariance. Step 4, following the guidance of Gunduz and Elsherbeny (2020), comprised model testing to evaluate the goodness of fit, parameters, and sample alignment. Finally, Step 5 involved model modification, wherein adjustments were made to enhance the fit through trimming or the introduction of new parameters. This comprehensive approach ensured the reliability and validity of the SEM analysis and provided a robust foundation for investigating the specified relationships and hypotheses within the research model.

This study removed non-critical items with factor-loading < 0.5 and chose a factor-loading threshold of 0.5 for variable elimination to retain strongly-related variables to the latent construct (Marsh et al., 2004). In line with Hair et al. (2014), convergent and divergent validity were used to validate the model. Convergent validity checks whether items of a variable contribute to variance, needing average variance extracted (AVE) of 0.05 or higher. AVE is calculated using the formula below:

$$AVE = \frac{\sum Standard\, Loading^2}{Number\, Of\, Indicators} \tag{2}$$

Divergent validity checked unrelated variables. Discriminant validity is confirmed if the square root of AVE exceeds the correlation between latent variables. After the above steps, the validated measurement model was used for SEM to test the research hypotheses.

RESULTS OF THE STUDY

Results of Demographic Analysis

A structured questionnaire was developed for demographic data collection, including position roles, years of working experience, and level of training in AI and finance. Figure 2 presents the demographic analysis of respondents from various Chinese financial institutions, which shows a diverse range of expertise. Notably, risk management officers exhibit the highest participation (20.9%), followed by financial analysts (18.1%) and senior investment bankers (15.3%). This distribution highlights the significance of risk assessment, financial analysis, and investment banking in AI-driven financial decision-making. Hedge fund managers (2.8%) and tax directors (4.0%) show lower participation, indicating their lesser prevalence among respondents. This diversity in expertise ensures a comprehensive understanding of ethical AI's impact across different financial functions to enhance the credibility, comprehensiveness, and applicability of this study.

Results of Descriptive Statistics and Relative Importance Index

Descriptive statistics, such as means and standard deviations, were computed to identify the major ethical challenges perceived by participants. The RII was then calculated to rank these challenges based on their perceived significance. The results of descriptive statistics analysis and RII are shown in Table 4.

Table 4 highlights critical AI ethics challenges in CFI. Leading the concerns are privacy and security issues (mean: 3.93, RII: 3.09). This is consistent with Xivuri & Twinomurinzi (2021) and Santosh and Wall (2022), who assert that ethical concern regarding data privacy and sensitive information exposure in AI-driven financial decision-making results in breaches of confidentiality,

Table 4. Results of descriptive statistics and relative importance index

	AI Ethics Challenges (AI_EC)	No.	Mean	Standard Deviation	Weights	RII	Rank
AI_EC1	Privacy and Security Issues	320	3.93	1.101	1258	3.09	1
AI_EC2	Inadequate Transparency	320	3.80	.949	1216	2.88	2
AI_EC3	Lack of Algorithmic Fairness	320	3.79	.939	1213	2.87	3
AI_EC4	Bias Detection Challenges	320	3.78	.910	1211	2.86	4
AI_EC5	Risk Assessment Limitations	320	3.77	1.009	1206	2.84	5
AI_EC6	Accountability Challenges	320	3.77	.936	1205	2.83	6
AI_EC7	Regulatory Compliance Hurdles	320	3.75	.944	1199	2.82	7
AI_EC8	Ethical Leadership Issues	320	3.75	.980	1199	2.81	8
AI_EC9	Data Quality Limitations	320	3.74	.911	1198	2.80	9
AI_EC10	Human Oversight Gaps	320	3.74	.845	1196	2.79	10
AI_EC11	Stakeholder Engagement Challenges	320	3.73	.961	1195	2.78	11
AI_EC12	Limited Explainability	320	3.71	.992	1187	2.77	12
AI_EC13	Data Governance Complexities	320	2.9	1.017	1182	1.90	13
AI_EC14	Insufficient Interpretability	320	2.7	1.432	987	1.89	14

compromised financial data, and a decline in customer trust. Following closely is inadequate transparency (mean: 3.80, RII: 2.88). Accordingly, Došilović et al. (2018) and Redrup Hill et al. (2023) postulate that a lack of transparency undermines the interpretability of AI systems, which poses a hindrance to stakeholders' understanding and trust. The third and fourth positions are occupied by a lack of algorithmic fairness (mean: 3.79, RII: 2.87) and bias detection challenges (mean: 3.78, RII: 2.86) with marginal differences. Tzimas (2021) and Balasubramaniam et al. (2020) support the findings. They emphasize how bias and unfairness perpetuate discriminatory outcomes and erode the ethical foundation of AI-driven financial decision-making in CFI. Conversely, data governance complexities (mean: 2.9, RII: 1.90) and insufficient interpretability (mean: 2.7, RII: 1.89) are comparatively less critical AI ethics challenges in CFI. While studies by Joseph (2020) and Lee (2020) underscore the significance of data governance in AI applications, this study suggests that in the context of CFI, these issues are less critical. To ensure data integrity, transparent decision-making, and fairness, it is vital to address these critical AI ethics challenges in CFI. As a result, this study establishes best practices to address the identified AI ethical challenges in financial decision-making within the CFI.

Convergent and Discriminant Validity

In Table 5, all AVEs for the variable surpassed the 0.5 threshold. As per Hair et al. (2014), an AVE of 0.5 or higher is considered acceptable for establishing convergent validity in the measurement model. This suggests that items within a variable adequately contribute to the variance, necessitating an AVE of 0.5 or above. Seven variables—RMC2, RMC3, FBM3, TE2, SEG1, SEG2, and DPS2—were removed due to low factor loading. To assess discriminant validity, the square root of AVE must exceed variable correlations (Crowson, 2020). Table 5 indicates that the square root of AVE, denoted as AV, exceeded the highest corresponding correlations with other constructs, which confirmed discriminant validity. The validated measurement model was subsequently used to test research hypotheses, leading to the development of the structural equation model.

Table 5. Convergent and discriminant validity of the measurement model

Latent Variables		Constructs	Standard Loadings	Standard Loadings²	The Sum of Standard Loadings²	No. of Variables	AVE	AV	Highest Correlations With Other Constructs
RMC5	<---	RMC	.666	0.5435	1.543	3	0.52	0.59	0.342
RMC4	<---	RMC	.693	0.5796					
RMC1	<---	RMC	.677	0.6595					
FBM5	<---	FBM	.657	0.8316	2.452	4	0.60	0.63	0.450
FBM4	<---	FBM	.686	0.9705					
FBM2	<---	FBM	.633	0.6006					
FBM1	<---	FBM	.716	0.5144					
TE5	<---	TE	.649	0.5212	2.561	4	0.64	0.26	0.034
TE4	<---	TE	.610	0.7721					
TE3	<---	TE	.651	0.4232					
TE1	<---	TE	.622	0.7868					
DPS5	<---	DPS	.631	0.9981	2.569	4	0.72	0.29	0.247
DPS4	<---	DPS	.632	0.7994					
DPS3	<---	DPS	.636	0.7056					
DPS1	<---	DPS	.605	0.6660					
SEG3	<---	SEG	.600	0.9600	1.578	3	0.52	0.43	0.330
SEG4	<---	SEG	.502	0.5520					
SEG5	<---	SEG	.606	0.9672					
AO5	<---	AO	.641	0.8116	3.045	5	0.64	0.48	0.41
AO4	<---	AO	.608	0.3696					
AO3	<---	AO	.663	0.8395					
AO2	<---	AO	.614	0.8769					
AO1	<---	AO	.599	0.8588					
EAI-FDM1	<---	EAI-FDM	.619	0.8831	2.53	5	0.67	0.70	0.46
EAI-FDM2	<---	EAI-FDM	.630	0.8969					
EAI-FDM3	<---	EAI-FDM	.622	0.9868					
EAI-FDM4	<---	EAI-FDM	.623	0.9881					
EAI-FDM5	<---	EAI-FDM	.624	0.5893					

Results of Structural Equation Model

Figure 3 illustrates the structural model, representing the AB-PraM for CFIs. Ohueri (2022) states that a significant p-value is deemed acceptable if other model fit indices fall within satisfactory thresholds. The comprehensive statistics of the structural model reveal an acceptable fit, which meets the recommended thresholds and induces model acceptance. Subsequently, hypotheses were tested (Table 6), revealing support for all seven hypotheses, which aligns with the stipulation of Hair et al. (2014) that the accepted p-value threshold should be ≤ 0.05.

All seven hypotheses in this study are substantiated (see Table 6). The research yields three important findings:

FBM, TE, DPS, and AO have a significant and positive impact on EAI-FDM among the financial experts in Chinese financial institutions.

Figure 3. Structural model with path weights

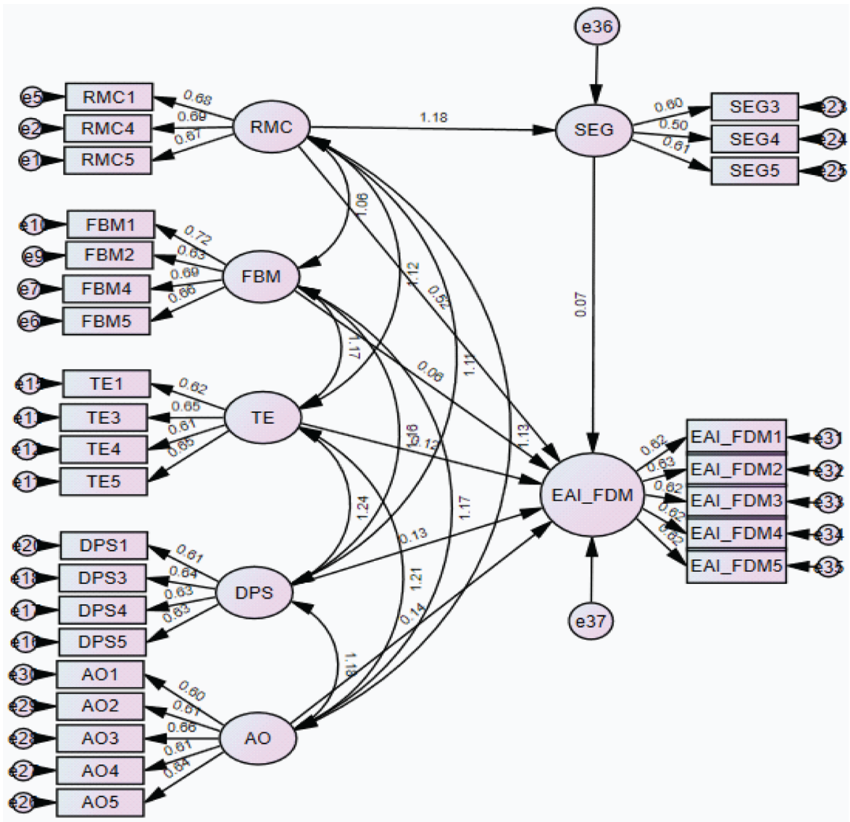


Table 6. Result of the tested hypotheses of this study

Hypotheses	Estimate	S.E.	C.R.	P	Remark
H1: RMC→EAI-FDM	.240	.059	3.768	0.04	Supported
H2: FBM→EAI-FDM	.390	.086	4.775	0.01	Supported
H3: TE→EAI-FDM	.159	.060	2.657	.008	Supported
H4: DPS→EAI-FDM	.125	.086	2.155	.041	Supported
H5: AO→EAI-FDM	.347	.069	1.2787	.022	Supported
H6: RMC→SEG→EAI-FDM	.125	.066	2.141	.034	Supported
H7: SEG→EAI-FDM	.157	.069	2.275	.023	Supported

RMC has a significant and positive impact on SEG and on EAI-FDM among the financial experts in Chinese financial institutions.

SEG has a significant and positive impact on EAI-FDM among the financial experts in Chinese financial institutions.

In contrast to prior research on AI in financial decision-making such as Fan et al. (2022), Gigante and Zago (2023), Chan et al. (2022), and Roberts et al. (2021), this study is the first, to the best of the authors' knowledge, to comprehensively integrate AI ethics best practices, an effort that strives to develop a model for ethical AI-driven financial decision-making explicitly tailored for CFIs. This research introduces the AB-PraM specifically designed for CFIs. The distinctive model addresses AI ethical challenges and fosters responsible AI usage in financial decision-making, an aspect that distinguishes it from prior studies in the field.

CONCLUSION

Despite the ever-growing prevalence of AI technology in financial institutions, there is a noticeable neglect of the ethical challenges associated with its rapid integration, which has raised serious apprehensions about potential adverse consequences including biased decisions, discriminatory outcomes, financial losses, and damage to reputations (Lin et al., 2023). To address the gap, this study employs a quantitative research method to develop the AB-PraM tailored for CFIs.

The findings indicate that AB-PraM comprises six vital categories: fairness and bias mitigation, transparent AI model documentation, data privacy and security, accountability and oversight, stakeholder engagement and governance, and risk management and compliance. With an emphasis on the interconnections of these ethical considerations in AI-driven financial decision-making, the study underscores the need for a holistic approach to address these challenges. The AB-PraM, with these facets encapsulated into a cohesive model, serves as a strategic roadmap that guides financial institutions to navigate the complex ethical terrain associated with AI. The identified mediator, stakeholder engagement and governance, accentuates the significance of the decision-making processes that involve all relevant parties. Recognizing the concerns and expectations of stakeholders, including customers, employees, and regulatory bodies, is integral to the construction of a resilient and ethically sound framework.

This research makes a primary contribution with implications for theory and practice. Theoretical implications involve a deeper understanding of ethics challenges in AI-driven financial decision-making within CFIs. The surge in AI-related investments in CFIs reflects a strategic drive for competitiveness yet introduces theoretical and managerial challenges in AI integration. For instance, ethical quandaries and the formulation of protocols to manage AI-generated insights pose considerable obstacles for CFIs heavily reliant on AI-driven decision-making. As such, the research serves as a practical tool for CFIs, as its outcomes offer actionable strategies for ethical AI application and guidelines for protocol development. Additionally, AB-PraM within CFIs exemplifies practical applications, given its direct solution to specific ethical concerns. For instance, recalibrating AI-driven credit scoring ensures fair approvals, transparent AI-powered investment recommendations instill trust, and ensuring data privacy in AI-driven customer service chatbots upholds confidentiality.

Furthermore, AB-PraM demonstrates its cultural and regulatory contribution to CFIs through the integration of values such as fairness and transparency, as it reflects China's collective ethos. For instance, AB-PraM guides AI decision-making to prioritize fairness in loan approvals, an aspect that aligns with Chinese cultural values of equity. It also maintains adaptability to regulatory shifts to ensure the compliance of the model with evolving regulations and the ethical expectations shaped by China's unique cultural structure. The model's capacity to balance cultural sensitivity and regulatory adherence is essential for the implementation of AI ethics best practices, since it aims to foster responsible and culturally-aligned AI use in China's financial industry.

Despite valuable insights yielded by the study into the practical implications of the integration of AI into financial decision-making processes, it is essential to acknowledge certain limitations that may influence the generalizability of the findings. Despite the proposed AB-PraM, the complete elimination of biases and discrimination in AI systems remains a challenge. For instance, in the context of CFIs, the intricate interplay of cultural nuances and evolving ethical standards may introduce unforeseen ethical dilemmas which are not addressable for the model. Additionally, the applicability of AB-PraM might be constrained outside the Chinese financial landscape, as different regulatory environments, cultural contexts, and financial practices could necessitate tailored approaches.

Ethical considerations specific to Western financial institutions, for instance, may vary. Therefore, it is necessary to conduct region-specific modifications to any overarching ethical framework. Future studies can explore external governance on the AI practices of CFIs, which can complement the AB-PraM introduced in this research. Furthermore, the comparable study between China and Western countries can provide a more nuanced understanding of the solutions for AI practices under different cultural and financial systems.

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