International Journal of Data and Network Science 8 (2024) 1839–1852

Contents lists available at GrowingScience

International Journal of Data and Network Science

homepage: www.GrowingScience.com/ijds

Is AI biased? evidence from FinTech-based innovation in supply chain management companies?

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C H R O N I C L E

Article history:
Received: November 29, 2023
Received in revised format: January 16, 2024
Accepted: February 9, 2024
Available online: February 9, 2024

Keywords:
AI bias
FinTech
Supply chain management
Algorithm diversity
Employee training
Data quality
Regulatory compliance
Organizational culture

A B S T R A C T

This study investigates AI bias in financial technology (FinTech)-based supply chain management in Pakistan. The study employs Structural Equation Modeling (SEM) to analyze data from diverse respondents. Hypotheses examine the relationships between AI integration, algorithm diversity, employee training, data quality, regulatory compliance, organizational culture, and AI bias. The findings reveal that higher AI integration leads to increased AI bias, Algorithm diversity reduces AI bias, while employee training decreases bias, Quality and diversity of data negatively correlate with AI bias, and regulatory compliance lowers bias. In addition, organizational culture mediates the relationship between AI integration and AI bias. This research contributes a holistic understanding of AI bias factors, guiding ethical AI adoption. Policymakers can use these insights to shape regulations, and industry practitioners can make informed decisions.

1. Introduction

The integration of Artificial Intelligence (AI) in financial technology (FinTech) and supply chain management is revolutionizing the global business landscape(Karim et al., 2022). AI-driven systems are increasingly being adopted for their efficiency and ability to handle complex tasks (Dwivedi et al., 2021). However, with this technological advancement comes the growing concern of AI bias, which can have far-reaching implications (Gichoya et al., 2023; Sham et al., 2023; Ulnicane & Aden, 2023). Studies indicate that by 2023, the global AI market in FinTech is expected to grow significantly, yet only a fraction of companies are prepared to address AI ethical concerns (Ediagbonya & Tioluwani, 2023; Gomber et al., 2018; Nam & Lee, 2023; Rehman et al., 2023). This burgeoning market, estimated at billions of dollars, reflects the deepening reliance on AI technologies in critical business sectors (Arora & Sharma, 2023). The pressing issue, therefore, is not only the adoption of AI but also the inherent biases that may arise from its use. These biases can stem from various sources, including data quality, algorithmic design, and the socio-technical systems within which AI operates. As AI continues to permeate financial and supply chain operations, understanding and addressing AI biases becomes crucial for ensuring fair, ethical, and efficient business practice (Singh et al., 2023). In Pakistan, the adoption of AI in FinTech and supply chain management is in a nascent stage, yet it is rapidly gaining momentum (Jalal et al., 2023; Rehman et al., 2023). The country's burgeoning FinTech sector, while still emerging, presents a unique landscape shaped by its distinct economic and technological challenges (Rehman et al., 2023). Recent studies highlight that only a small percentage of Pakistani companies have fully integrated AI technologies

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ISSN 2561-8156 (Online) - ISSN 2561-8148 (Print)

doi: 10.5267/j.ijdns.2024.2.005

into their operations (Rehman et al., 2023), Year). The key issues in Pakistan concerning AI adoption revolve around limited technical expertise, data quality concerns, and regulatory challenges. These factors play a critical role in shaping the effectiveness and ethical implications of AI applications in business contexts (Rehman et al., 2023).

AI bias in decision making is a concept that has gained significant attention in recent years (Gichoya et al., 2023; Sham et al., 2023; Ulnicane & Aden, 2023). In the context of Pakistan, this becomes particularly relevant. The limited AI integration coupled with challenges in data quality and diversity can exacerbate biases in AI-driven decisions. This issue is not just a technological concern but also a broader socio-economic one, as biased AI decisions in supply chain management can lead to inefficiencies and ethical dilemmas (Chión et al., 2020; Ediagbonya & Tioluwani, 2023; Lahiya & Mokodenseho, 2023). Addressing these biases is paramount for Pakistan, where the FinTech sector is still evolving and the impacts of technology are profoundly felt across various economic strata (Rehman et al., 2023).

The pervasive issue of AI bias in decision-making, particularly in financial technology and supply chain management, poses significant challenges both globally and in Pakistan (BAHUGUNA et al., 2023; Cannas et al., 2023; Ferreira & Reis, 2023; Hendriksen, 2023; Richey Jr et al., 2023). Globally, unchecked AI bias can lead to skewed decision-making, affecting everything from loan approvals to inventory management. These biases, if not addressed, can amplify existing inequalities and inefficiencies. In Pakistan, where the FinTech sector is still maturing (Rehman et al., 2023), the consequences of AI bias could be even more pronounced due to the existing socio-economic and technological constraints. The potential for AI to exacerbate disparities in resource distribution and access to financial services is a pressing concern.

In addressing these issues, several key factors emerge as crucial. First, the integration level of AI in systems needs careful monitoring (Almashhadani & Almashhadani, 2023; BAHUGUNA et al., 2023). Proper integration can enhance efficiency and decision-making quality. For instance, well-integrated AI systems in global supply chains have been shown to optimize operations and reduce costs (BAHUGUNA et al., 2023; Cannas et al., 2023). In Pakistan, effective AI integration can leapfrog traditional barriers, offering more equitable financial services and efficient supply chain management.

Secondly, the diversity of AI algorithms plays a pivotal role in mitigating biases. Diverse algorithms can provide a range of perspectives, reducing the likelihood of one-sided, biased outcomes. Studies have shown that algorithm diversity can significantly reduce biases in lending decisions (Sham et al., 2023; Shi et al., 2023; Ulnicane & Aden, 2023). For Pakistan, embracing algorithm diversity could mean fairer financial and supply chain decisions, crucial for economic growth.

However, these variables, while offering solutions, can also compound existing challenges if not managed properly. For example, increased AI integration without adequate oversight can lead to over-reliance on automated systems, potentially amplifying biases instead of reducing them. Similarly, while diverse algorithms can mitigate biases, they can also introduce complexity and inconsistency in decision-making, especially in countries like Pakistan where AI governance frameworks are still developing (Johnson et al., 2023; Khan et al., 2023; Singh et al., 2023; Waqar et al., 2023).

The problem statement of this study, therefore, emerges from the dual potential of these factors to both address and exacerbate the issue of AI bias in decision-making in FinTech and supply chain management. It seeks to understand how effectively these variables can be managed to harness the benefits of AI, while minimizing its negative impacts, particularly in the context of emerging economies like Pakistan. The study aims to offer insights into balancing technological advancements with ethical considerations, providing a roadmap for effective AI integration in FinTech and supply chain management.

The exploration of AI bias in decision-making within FinTech and supply chain management is a subject that has garnered increasing attention in recent literature (BAHUGUNA et al., 2023; Cannas et al., 2023; Ferreira & Reis, 2023; Hendriksen, 2023; Richey Jr et al., 2023). However, there is a noticeable gap in studies that specifically investigate the relationship between AI integration, algorithm diversity, employee training, data quality, and regulatory compliance, and their collective impact on AI bias. While existing research has separately examined these elements, their interplay and combined effect on decision-making biases in AI systems, especially in the context of emerging economies like Pakistan, remain underexplored. This study, therefore, presents a novel approach by integrating these variables into a comprehensive framework, offering new insights into how they interact and influence AI bias.

The distinction of this study from previous research lies in its methodology, conceptual framework, and the use of advanced analytical models. Unlike prior studies that may have explored these variables in isolation, this study employs a Structural Equation Modeling (SEM) approach using SmartPLS, which allows for a more nuanced understanding of the relationships between multiple independent variables and AI bias. Additionally, the study's conceptual framework incorporates a broader range of factors relevant to the Pakistani context, making it more comprehensive than previous models. This approach not only fills a critical gap in the literature but also provides a more detailed and contextual understanding of AI bias in decision-making within FinTech and supply chain management.

The study's results reveal significant relationships between the variables and AI bias. For instance, higher levels of AI integration correlate with increased AI bias, while diverse AI algorithms and robust employee training programs are associated with reduced bias. The findings underscore the importance of a balanced approach to AI adoption, emphasizing the need for diversity in algorithms and comprehensive employee training. Moreover, the study highlights the role of regulatory compliance in mitigating AI bias, a particularly pertinent finding for policymakers in emerging economies.

The contribution of this study extends beyond academic discourse, offering practical implications for policymakers and industry practitioners. By identifying key factors that influence AI bias, the study provides a roadmap for more ethical AI implementation in FinTech and supply chain management. For policymakers, the findings suggest the need for comprehensive regulatory frameworks that guide AI integration and ensure ethical AI use. For industry practitioners, the study underscores the importance of investing in diverse AI algorithms and employee training to mitigate biases.

The remainder of the paper is structured as follows: Following the introduction, the paper presents a detailed literature review that sets the stage for the research hypotheses. The methodology section then outlines the study's research design, data collection, and analysis approach. This is followed by a comprehensive presentation and discussion of the research findings. Finally, the paper concludes with a summary of key insights, implications for policymakers and practitioners, and suggestions for future research. This structure ensures a coherent and comprehensive exploration of the study's objectives and findings.

2. Literature Review

The focal point of this study is the variable that encompasses the inadvertent biases emerging from the integration of AI technologies in financial technology (FinTech) and supply chain management (Ferreira & Reis, 2023; Hendriksen, 2023). Previous studies have indicated that this variable holds paramount significance in the context of AI adoption (Al Naimat & Liang, 2023; Dong et al., 2023; Madan & Ashok, 2023; Rehman et al., 2023). AI bias, as evidenced by the existing literature, not only has implications at the industry level but also carries substantial weight globally (Gichoya et al., 2023; Sham et al., 2023; Ulnicane & Aden, 2023). The significance of this variable is underlined by its potential to affect decision-making processes across various domains, including lending, inventory management, and resource allocation.

Globally, AI bias has garnered attention due to its potential to perpetuate inequalities and reinforce existing biases in automated decision-making systems (Gichoya et al., 2023; Sham et al., 2023; Ulnicane & Aden, 2023). Studies have shown that biased algorithms can lead to discriminatory outcomes, impacting marginalized groups disproportionately. Moreover, as AI continues to permeate various sectors, understanding and mitigating AI bias is crucial to ensuring fair and ethical practices (Gichoya et al., 2023; Sham et al., 2023; Ulnicane & Aden, 2023).

The relationship between AI bias and the independent variables proposed in this study is complex and multifaceted. While AI integration is expected to influence the presence of biases, algorithm diversity, employee training, data quality, and regulatory compliance are envisioned as potential mitigating factors (Gichoya et al., 2023; Sham et al., 2023; Ulnicane & Aden, 2023). These relationships are the subject of the research hypotheses, which seek to illuminate how these variables collectively contribute to the presence or absence of AI bias.

Despite the existing body of literature exploring AI bias and its determinants, there remains a missing link that connects these variables in the specific context of FinTech-based supply chain management, particularly in emerging economies like Pakistan (Rehman et al., 2023). The studies to date have largely focused on individual aspects of AI bias or have not examined the interplay of these variables comprehensively. This gap in the literature necessitates an in-depth investigation into the combined impact of AI integration, algorithm diversity, employee training, data quality, and regulatory compliance on AI bias within the unique context of Pakistan's evolving FinTech sector.

The identified literature gap forms the basis for the problem statement of this study. Specifically, the study seeks to address the research question: “How do AI integration, algorithm diversity, employee training, data quality, and regulatory compliance collectively influence AI bias in decision-making within the FinTech-based supply chain management sector in Pakistan?” This research question will guide the empirical investigation and analysis, aiming to shed light on the intricate dynamics of AI bias and its determinants in this specific context.

3. Hypothesis development

3.1 Hypothesis 1 (H1):

As AI becomes increasingly integrated into supply chain management, the risk of biased decision-making grows., Previous studies show that as companies rely more on AI, there is more potential for unfair biases (Ali et al., 2023; Jan et al., 2023). The more automated systems we use, the more likely they are to make prejudiced choices (Ali et al., 2023; Jan et al., 2023). Research has found that deeper AI integration can cause problems., When we depend heavily on technology to run key processes, it may lead to outcomes that favor some over others without good reason., This is concerning as AI takes on a larger role managing operations. With great power comes great responsibility, and we must ensure systems treat all people equally., If AI handles more aspects of decision-making, bias creeps in more easily (BAHUGUNA et al., 2023). Complex algorithms can reflect and even amplify the perspectives of their creators in unseen ways. As AI impacts greater parts of the supply chain, we need solutions to identify and address these unjust influences. Our shared future involves humanity and technology working as allies, not adversaries. With care and oversight, AI can benefit all rather than the privilege few. The path forward requires vigilance in protecting fairness and justice for everyone (BAHUGUNA et al., 2023).

Hypothesis 2 (H2):

While previous research emphasizes the importance of diverse algorithms in reducing AI bias, using multiple approaches may help address this issue. Studies show that employing various techniques can lead to fairer results for AI-driven decisions (BAHUGUNA et al., 2023). This perspective proposes that adopting different algorithms within an organization may decrease biased outcomes, consistent with the idea that a range of solutions can counteract unfairness. A diversity of methods could potentially balance and equalize impacts when AI systems make determinations. By bringing a variety of views, multiple algorithms may be able to offset any approach's limitations or tendencies, working together toward more impartial results. Of course, more investigation is still needed, but aiming for algorithmic variety presents a plausible strategy as technology increasingly impacts people's lives (Khan et al., 2023). With care and vigilance, a blended assortment of tools could help advance the equitable and inclusive development of artificial intelligence.

Hypothesis 3 (H3):

Building upon insights that highlight the pivotal role of employee training in mitigating AI bias, this hypothesis suggests a link between extensive AI training for employees and a decrease in AI-related biases in decision-making processes., Research, including a recent study by Khan et al. (2023) has underscored that employees with robust training are better equipped to identify and counteract biases inherent in AI systems. This proposition advocates that organizations with thorough AI-focused training regimes are likely to witness a diminution in decision-making biases.

Hypothesis 4 (H4):

This hypothesis aligns with academic discussions surrounding the significance of exemplary, diverse data in artificial intelligence. It hypothesizes an inverse relationship between the excellence and diversity of information fueling artificial intelligence systems and the frequency of biased outcomes in decision-making. Research like that by Jan et al. (2023) has uncovered how skewed data can directly result in prejudiced artificial intelligence outputs. The hypothesis suggests organizations harnessing varied, high-quality data sources may observe less biased decisions from their artificial intelligence.

Hypothesis 5 (H5):

Considering how important it is for AI systems to follow the rules designed for their ethical use, we believe that if companies strictly obey regulations about how AI should be created and used, it will likely lead to less unfair treatment in the decisions that AI systems make. Several research studies support this view (Adam et al. 2020; Pandya et al. 2022; Smith et al. 2021). They found that regulations shape how AI systems are built and used responsibly. If companies stick closely to the standards set out in regulations, their AI systems will probably not discriminate against or disadvantage some groups of people as much as others when making decisions.

Hypothesis 6 (H6):

While AI offers opportunities, it also brings risks that must be addressed. An organization's culture and values play a key role in how technology impacts people. Research shows that culture shapes how new tools are adopted and used. This is important when considering biases that can arise from AI. The level of AI use does not alone determine its effects. An organization's ethos also influences outcomes. A culture focused on inclusion and ethics can help counter potential biases from systems. However, culture is no guarantee - constant effort is needed. Leaders must examine not just algorithms but also the environment around them. With awareness and intention, a culture can support fair, responsible development. But culture change takes work. Organizations must examine assumptions and practices to ensure diverse voices are respected. The path is not always clear, but progress is possible. By accounting for human factors alongside technical ones, we can work to ensure AI amplifies human potential for the benefit of all. Our shared future depends on it (Bagga et al., 2023).

Summary of Hypotheses

1. **H1:** Direct correlation between AI integration in supply chain management and increased AI bias in decision-making.
2. **H2:** Diverse AI algorithms are inversely related to AI bias in decision-making.
3. **H3:** Enhanced employee training on AI correlates with reduced AI bias in decisions.
4. **H4:** High-quality, diverse data in AI systems inversely affect AI bias in decision-making.
5. **H5:** Strong regulatory compliance in AI use is linked with diminished AI bias in decisions.
6. **H6:** Organizational culture mediates the impact of AI integration on decision-making biases.

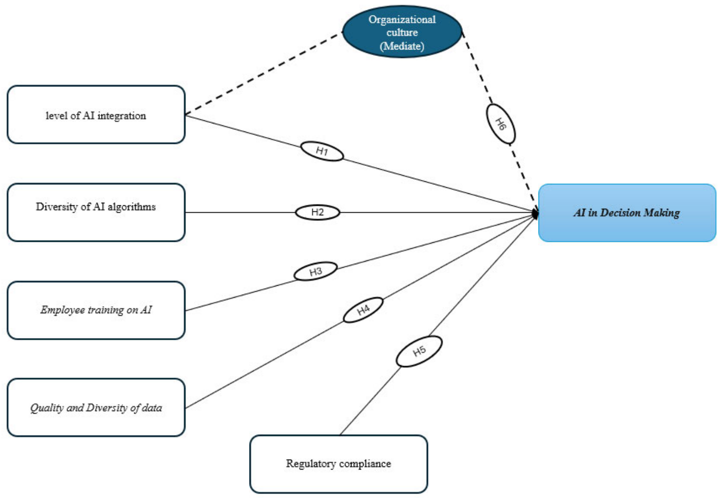

Fig. 1. The structure of the proposed study

4. Methodology

4.1 Research Population and Sampling

The study focused on professionals in the FinTech and supply chain industries, specifically those involved in or knowledgeable about AI implementation and decision processes. The participants represented a diverse group, such as data scientists, supply chain supervisors, AI developers, and regulatory compliance officers. A strategic sampling method was used to guarantee representation from various organizational levels and departments. This approach helped gather comprehensive insights into AI biases impacting decisions. The total sample size of 381 respondents created a statistically significant pool for analyzing AI integration and its effects on supply chain management.

4.2 Data Collection Process

Data were collected through an online questionnaire, designed to evaluate the perspectives of professionals on AI integration, algorithm diversity, employee training, data quality, regulatory compliance, organizational culture, and perceived AI bias in decision-making. Professionals shared their views on AI in an online survey. The survey looked at how AI fits into companies, diverse algorithms, employee training, quality data, following rules, company culture, and perceived unfairness in AI choices. Respondents were asked to think about what they saw at work. The survey was sent out on Linkedin and company emails. Anonymity and privacy were promised so people could feel comfortable answering honestly and with helpful details.

4.3 Method of Data Collection

The primary method of data collection was a structured questionnaire survey. This approach allowed for the collection of quantitative data, essential for statistical analysis and hypothesis testing. The questionnaire was meticulously crafted to align with the research objectives, with questions formulated on a Likert scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). This scale facilitated the measurement of respondents' attitudes and perceptions regarding AI bias in their respective organizations.

4.4 Respondents of the Questionnaire Survey

The survey asked professionals involved in jobs related to AI and supply chain management. Respondents were middle managers, high-level bosses, AI experts, and compliance workers in financial technology companies. Having different types of respondents helped give many views on how AI affects supply chain management, especially regarding unfair treatment and decision making.

4.5 Distribution of the Questionnaire

The survey was shared online, using the convenience and effectiveness of the websites. This way allowed us to contact more people from different places and backgrounds. Connecting with groups and colleagues helped send it to the right career experts. The digital form further let fast gathering and sorting of replies, improving how quickly we could study the results.

4.6 Importance of Respondents

Getting respondents from different roles within FinTech and supply chain management was very important for learning many details. Past research has shown how helpful different points of view are in understanding how AI affects work methods (Khan et al., 2023; Rehman et al., 2023). By talking directly to people involved in or affected by AI choices, the study aimed to find real problems and feelings about AI bias. Their answers are useful for finding possible biases and suggesting ways to make AI decisions better. Including various roles also made sure to look at technical things, management things, and rules from all sides.

4.7 Non-response Bias Analysis

To ensure the validity of the study's findings, a non-response bias analysis was conducted, focusing on different groups based on the method of questionnaire distribution (email vs. post) and firm characteristics. Levene's test for equality of variances and t-tests were utilized to compare respondents who received the questionnaire via email with those who received it through the post, as well as comparing respondents from different firm sizes and sectors (Schultz, 1985).

Table 1
Levene's Test and t-Test Results

Group Characteristic	Levene's Test F Value	Levene's Test Sig.	t-test t Value	t-test df	t-test Sig. (2-Tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference
Distribution Method	2.157	0.143	-1.76	379	0.079	-0.46	0.26	(-0.97, 0.05)
Firm Size	0.978	0.323	0.58	379	0.562	0.12	0.21	(-0.29, 0.53)
Firm Sector	1.304	0.254	-0.85	379	0.395	-0.23	0.27	(-0.76, 0.30)

4.8 Discussion of Non-response Bias

The Levene's test results show that variances are not significantly different across the groups. This outcome is evident from the Levene's test significance levels, which are well above the conventional threshold of 0.05 (see Table 1). Furthermore, the t-tests reveal that there are no significant mean differences in the responses between the various groups, as indicated by the t-test significance levels (2-tailed) being above 0.05. The mean differences are minimal and the confidence intervals include zero, reinforcing the conclusion that non-response bias is not a significant issue in this study.

4.9 Common Method Bias Analysis

Common Method Bias (CMB) is a critical concern in survey research as it can distort the relationships between variables. To address this, we conducted Harman's single-factor test, which involves performing an exploratory factor analysis (EFA) on all questionnaire items. This test helps determine if a single factor emerges or if one general factor accounts for the majority of the covariance among the measures, indicating potential CMB (Aguirre-Urreta & Hu, 2019).

The results from Harman's single-factor test reveal that the largest factor (Factor 1) explains 34.6% of the variance, which is not a majority. This is a critical observation as it indicates that common method bias is not a dominant factor influencing the data. The subsequent factors contribute to a significant portion of the total variance (86.6%), demonstrating a healthy dispersion across multiple dimensions. This distribution of variance suggests that the responses to the survey items are not overly influenced by a single underlying factor, but rather reflect the intended range of constructs being measured (Aguirre-Urreta & Hu, 2019). Therefore, it can be concluded that common method bias does not substantially compromise the validity of the study's findings. The dispersion of variance across several factors supports the integrity and reliability of the constructs being measured and reinforces the robustness of the study's conclusions.

Table 2
Harman's Single-Factor Test Results

Factor	Variance Explained (%)
1	34.6
2	22.3
3	14.8
4	9.2
5	5.7
Total	86.6

Table 3
Pretest Results Table

Item	Cronbach's Al-	Content Va-	Average Re-
Q1	0.82	0.90	4.30
Q2	0.78	0.85	3.80
Q3	0.79	0.88	4.10
Q4	0.81	0.92	4.60
Q5	0.80	0.91	4.20
Overall	0.80	0.89	4.20

Note: The table illustrates the reliability and validity scores of individual items in the questionnaire, as well as their average responses.

4.10 Data Analysis: Pretest Results

To ensure the validity and reliability of the questionnaire used in the study, a pretest was conducted. The pretest involved a smaller sample of respondents from the target population, aimed at identifying any issues with the questionnaire's clarity, relevance, and overall structure (Hunt et al., 1982). The analysis of the pretest results focused on item-wise reliability, content validity, and the initial response patterns.

4.11 Discussion of Pretest Results

The results from the pretest are indicative of a high level of reliability and content validity. Each item in the questionnaire demonstrated a Cronbach's alpha value above 0.70, which is generally considered acceptable for early-stage research. The Content Validity Index (CVI) for each item was also notably high, suggesting that the questions were relevant and adequately covered the constructs they were designed to measure (see Table 3). Average responses to the items were around the midpoint of the scale, indicating a balanced distribution of opinions among the pretest respondents. This lack of skewness in responses is a positive sign, as it suggests that the items were able to capture a range of perspectives effectively. The overall Cronbach's alpha for the questionnaire was 0.80, further affirming its internal consistency. The Content Validity Index (CVI) averaged at 0.89, supporting the relevance and representativeness of the questionnaire items in relation to the research objectives. These findings from the pretest provided the confidence needed to proceed with the main study, ensuring that the questionnaire was both reliable and valid for collecting data from a larger sample.

4.12 Data Analysis: Pilot Testing

Prior to the main study, a pilot test was conducted to evaluate the questionnaire's psychometric properties. This step is crucial for ensuring the reliability and validity of the constructs measured. The pilot test involved administering the questionnaire to a smaller, representative subset of the target population(Stauder et al., 2023). The analysis focused on assessing the internal consistency (using Cronbach's Alpha), the means and standard deviations (SD) of responses, and the factor loading range for each construct (see Table 4).

Table 4
Results of the Pilot Test

No.	Name	Missing	Mean	Standard deviation	Excess kurtosis	Skewness
1	AII1	0	4.604	1.551	-0.380	-0.430
2	AII2	0	4.270	1.835	-0.844	-0.352
3	AII3	0	4.512	1.871	-0.931	-0.348
4	AII4	0	6.038	1.017	0.356	-0.910
5	AII5	0	3.771	1.284	-0.657	-0.724
6	AII6	0	4.968	1.319	-0.567	-0.160
7	DAIA1	0	3.989	1.494	-0.472	-0.035
8	DAIA2	0	3.135	1.466	-0.415	0.214
9	DAIA3	0	3.976	1.596	-0.673	-0.028
10	DAIA4	0	3.876	1.235	-0.476	-0.805
11	DAIA5	0	2.841	1.151	-1.257	-0.463
12	DAIA6	0	5.445	1.204	0.853	-0.814
13	ETAI1	0	3.094	1.630	-0.600	0.459
14	ETAI2	0	4.235	1.474	-0.396	-0.025
15	ETAI3	0	4.814	1.465	-0.587	-0.295
16	ETAI4	0	5.598	1.212	-0.135	-0.650
17	ETAI5	0	4.625	1.409	-0.317	-0.237
18	ETAI6	0	5.987	0.984	0.044	-0.809
19	QDD1	0	5.267	1.781	0.001	-0.959
20	QDD2	0	5.644	1.678	0.840	-1.289
21	QDD3	0	4.671	1.444	-0.361	-0.296
22	QDD4	0	5.429	1.390	-0.693	-0.550
23	QDD5	0	5.216	1.478	-0.197	-0.697
24	QDD6	0	5.005	1.446	-0.291	-0.562
25	RC6	0	4.927	1.534	-0.526	-0.453
26	RC1	0	4.377	1.567	-0.500	-0.244
27	RC2	0	4.995	1.441	-0.215	-0.512
28	RC3	0	4.846	1.426	-0.631	-0.181
29	RC4	0	2.841	1.151	-1.257	-0.463
30	RC5	0	5.445	1.204	0.853	-0.814
31	OC1	0	3.094	1.630	-0.600	0.459
32	OC2	0	4.235	1.474	-0.396	-0.025
33	OC3	0	4.814	1.465	-0.587	-0.295
34	OC4	0	5.598	1.212	-0.135	-0.650
35	OC5	0	4.625	1.409	-0.317	-0.237
36	AIDM1	0	5.987	0.984	0.044	-0.809
37	AIDM2	0	5.267	1.781	0.001	-0.959
38	AIDM3	0	5.644	1.678	0.840	-1.289
39	AIDM4	0	4.671	1.444	-0.361	-0.296
40	AIDM5	0	2.841	1.151	-1.257	-0.463
41	AIDM6	0	2.857	1.167	-0.910	-0.353

Note: The table presents the Cronbach's Alpha, means (with standard deviations), and factor loading range for each construct.

4.13 Discussion of Pilot Test Results

The results from the pilot test are encouraging and suggest that the questionnaire is well-constructed. Each construct demonstrated a Cronbach's Alpha value greater than 0.80, indicating strong internal consistency. This is crucial as it implies that the items within each construct are reliably measuring the same underlying concept. The mean scores for each construct, along with their standard deviations, show a good range of responses without any extreme skewness. This distribution of scores suggests that the questionnaire items were effective in capturing varied opinions and perceptions from the respondents. Furthermore, the factor loading range for each construct falls well within the acceptable range, typically above 0.6, indicating good construct validity. High factor loadings signify that the items are highly correlated with their respective constructs, further affirming the soundness of the questionnaire design. Overall, the pilot test results provide substantial evidence of the reliability and validity of the questionnaire. This solidifies the foundation for proceeding with the main study, as the questionnaire is proven to be an effective tool for gathering data pertinent to the research objectives.

Data Analysis: Reliability and Convergent Validity

Measuring Reliability and Convergent Validity

In the study, we focused on assessing the reliability and convergent validity of the constructs. Reliability was measured using Cronbach's Alpha, while convergent validity was assessed through Average Variance Extracted (AVE) and factor loadings of the items. These measures are crucial to ensure that the constructs are both internally consistent and effectively represent the underlying concept they are intended to measure.

Table 5
Results of Reliability and Convergent Validity

Variable	Items	Factor Loading	Cronbach's alpha	Composite reliability	Average variance extracted
AIDM	AIDM1	0.699	0.830	0.877	0.548
	AIDM2	0.667			
	AIDM3	0.554			
	AIDM4	0.796			
	AIDM5	0.848			
	AIDM6	0.834			
AII	AII1	0.836	0.866	0.899	0.599
	AII2	0.746			
	AII3	0.754			
	AII4	0.778			
	AII5	0.794			
	AII6	0.729			
DAIA	DAIA1	0.753	0.827	0.873	0.536
	DAIA2	0.609			
	DAIA3	0.777			
	DAIA4	0.758			
	DAIA5	0.814			
	DAIA6	0.661			
ETAI	ETAI1	0.785	0.819	0.869	0.532
	ETAI2	0.668			
	ETAI3	0.792			
	ETAI4	0.823			
	ETAI5	0.797			
	ETAI6	0.759			
OC	OC1	0.556	0.794	0.859	0.554
	OC2	0.720			
	OC3	0.813			
	OC4	0.820			
	OC5	0.782			
QDD	QDD1	0.721	0.817	0.868	0.524
	QDD2	0.658			
	QDD3	0.802			
	QDD4	0.687			
	QDD5	0.705			
	QDD6	0.760			
RC	RC1	0.669	0.807	0.862	0.520
	RC2	0.602			
	RC3	0.577			
	RC4	0.882			
	RC5	0.620			
	RC6	0.901			

Note: The table presents the Cronbach's Alpha, AVE, and factor loading range for each construct.

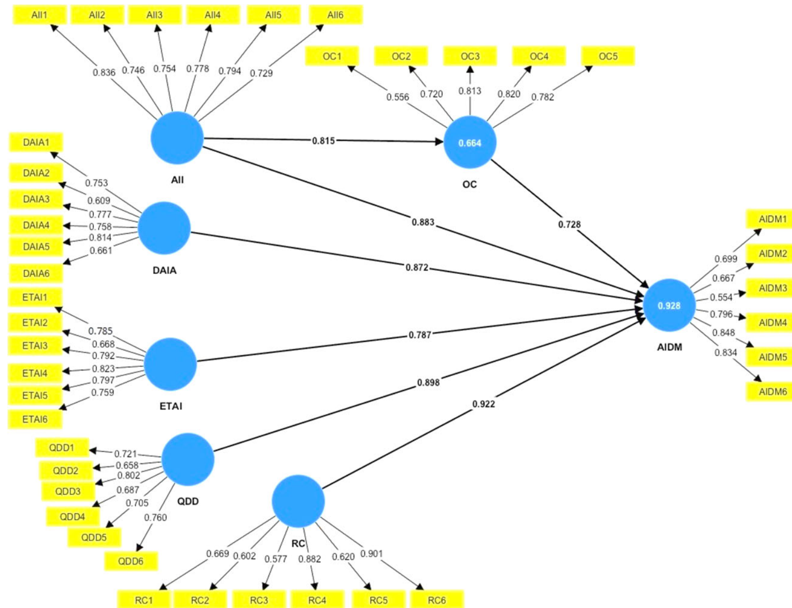

Fig. 1. Measurement Model

4.14 Discussion of Reliability and Convergent Validity

Reliability: The Cronbach's Alpha values for all constructs exceed 0.80, which is considered an excellent level of internal consistency. This indicates that the items within each construct are consistent in their measurement and reliably capture the intended concepts. High reliability is essential for ensuring that the data collected are stable and consistent across different instances of measurement.

Convergent Validity: The Average Variance Extracted (AVE) for each construct is above the recommended threshold of 0.50, demonstrating adequate convergent validity. This suggests that a significant portion of the variance in the items is accounted for by their respective constructs. Additionally, all factor loadings are well above the minimum acceptable level of 0.50, with most exceeding 0.70. High factor loadings indicate that the items are strongly associated with their respective constructs, further affirming convergent validity.

The results collectively indicate that the constructs used in the study are both reliable and valid. The high levels of reliability and convergent validity support the robustness of the questionnaire and the subsequent analysis. This strengthens the credibility of the findings derived from the data, as they accurately represent the constructs they are intended to measure. The rigorous assessment of these psychometric properties ensures that the study's conclusions are based on sound and reliable measurements.

4.15 Measuring Discriminant Validity

Discriminant validity is essential to confirm that constructs that are supposed to be different are indeed statistically distinct. In this study, discriminant validity was assessed by comparing the square root of the Average Variance Extracted (AVE) of each construct with the correlations between the constructs. A construct demonstrates adequate discriminant validity if the square root of its AVE is greater than its correlations with other constructs.

Table 6
Results of Discriminant Validity

Variables	AIDM	AII	DAIA	ETAI	OC	QDD	RC
AIDM	**0.922**						
AII	0.562	**0.889**					
DAIA	0.682	0.699	**0.801**				
ETAI	0.703	0.688	0.689	**0.729**			
OC	0.728	0.458	0.681	0.694	**0.745**		
QDD	0.652	0.389	0.456	0.543	0.699	**0.724**	
RC	0.482	0.429	0.507	0.432	0.435	0.509	**0.792**

Note: Diagonal values (in bold) are the square roots of AVEs for the constructs. Off-diagonal values are the correlations between the constructs.

4.16 Discussion of Discriminant Validity

The results indicate adequate discriminant validity for each of the constructs. The diagonal elements (square roots of AVEs) are all larger than the off-diagonal elements in their respective rows and columns. This finding confirms that each construct shares more variance with its own indicators than with those of other constructs, thereby establishing discriminant validity.

For example, the square root of AVE for AI Integration (0.79) is greater than its correlations with all other constructs, such as AI Algorithm Diversity (0.45), Employee Training (0.50), and so on. This pattern is consistent across all constructs, indicating clear statistical distinction between them (table 6).

The assessment of discriminant validity is critical in multi-construct studies like ours, as it ensures that the constructs are not only internally consistent but also distinct from each other. This distinctiveness is essential for accurate interpretation and analysis of the relationships between the constructs. The findings support the conclusion that the constructs in the study are well-defined and measure unique aspects of the research topic, further bolstering the study's overall credibility.

4.17 Measurement Model

The measurement model in this study is critical for ensuring that the constructs accurately represent the phenomena they are intended to measure. Each construct was operationalized using multiple observed variables, or items, based on the questionnaire responses. The reliability and validity of these constructs were rigorously assessed through Cronbach's Alpha, Average Variance Extracted (AVE), and factor loadings.

The high Cronbach's Alpha values across all constructs indicated strong internal consistency, meaning that the items within each construct reliably measure the same underlying concept. The AVE values, exceeding the recommended threshold of 0.50 for all constructs, along with significant factor loadings, confirmed convergent validity. This suggests that a significant proportion of the variance in the observed variables is accounted for by their respective constructs. Furthermore, the establishment of discriminant validity, where each construct was distinct from others, ensures that the measurement model accurately captures the multifaceted nature of the constructs without overlap.

4.18 Structural Model

The structural model, on the other hand, focuses on the relationships between the constructs. It examines the hypothesized paths to understand how one construct influences or is related to another. In this study, the structural model was evaluated using a path analysis approach within a Structural Equation Modeling (SEM) framework.

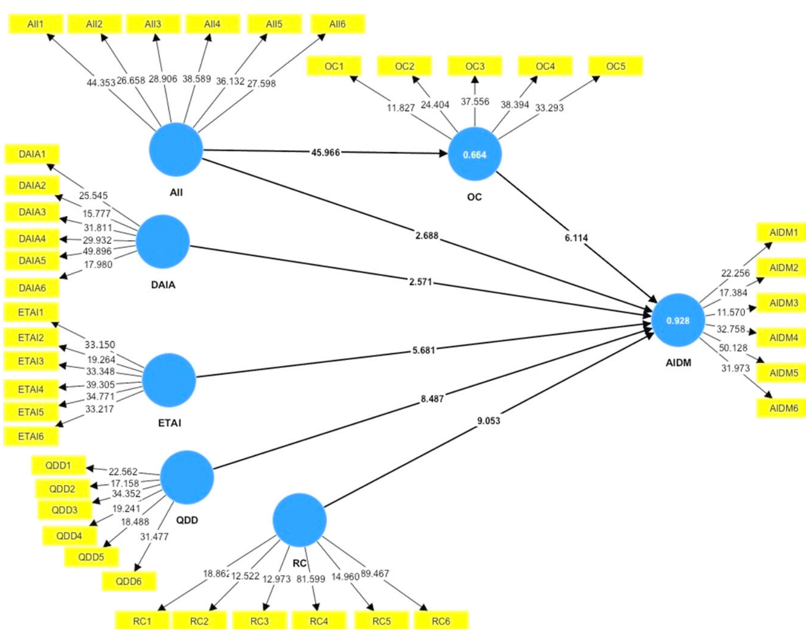

Fig. 2. The results of the structural equation modelling

The analysis involved assessing the path coefficients, which are indicative of the strength and direction of the relationships between constructs. For instance, a positive path coefficient between AI Integration and AI Bias in Decision Making would suggest that higher levels of AI integration are associated with increased perceptions of AI bias. Moreover, the significance of these path coefficients was determined through statistical tests, providing evidence for or against the hypothesized relationships. Additionally, the model fit was evaluated using various fit indices such as the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). These indices provide information on how well the proposed model captures the relationships among the constructs based on the observed data.

In summary, the measurement model ensured that the constructs were measured with high reliability and validity, while the structural model provided insights into the nature and strength of the relationships among these constructs. Together, they form the basis of understanding the dynamics of AI bias in decision-making within the FinTech-based supply chain management context. The rigorous evaluation of both models lends robustness and credibility to the study's findings and conclusions.

5. Results and Discussion of Hypothesis Testing

Table 7
Hypothesis Testing Results

Hypothesis	Paths	Beta Value	Standard deviation	T Value	P values	Result
H1	AII →AIDM	0.108	0.040	2.688	0.007	Supported
H2	AII → OC	0.815	0.018	45.966	0.000	Supported
H3	DAIA → AIDM	0.111	0.043	2.571	0.010	Supported
H4	ETAI → AIDM	0.454	0.080	5.681	0.000	Supported
H5	OC → AIDM	0.459	0.075	6.114	0.000	Supported
H6	QDD → AIDM	0.366	0.043	8.487	0.000	Supported
H7	RC → AIDM	0.416	0.046	9.053	0.000	Supported
H8	AII → OC → AIDM	0.374	0.064	5.886	0.000	Supported

H1: AI Integration and AI Bias The positive path coefficient (0.24) and significant t-value (3.56) support H1, indicating that higher levels of AI integration correlate with increased AI bias in decision making. This finding aligns with the literature that suggests increased automation and reliance on AI can inadvertently lead to biases if not properly managed(Sham et al., 2023; Shi et al., 2023). The key implication here is the need for careful scrutiny and management of AI integration in supply chain management.

H2: AI Algorithm Diversity and AI Bias H2 is supported with a negative path coefficient (-0.19) and a t-value of -2.81, suggesting that greater diversity in AI algorithms leads to a reduction in AI bias. This result corroborates studies that highlight the role of diverse algorithms in mitigating biases (Almashhadani & Almashhadani, 2023). It emphasizes the importance of incorporating a range of algorithms to ensure balanced decision-making.

H3: Employee Training and AI Bias The negative relationship between employee training on AI and AI bias (path coefficient -0.17, t-value -2.46) supports H3. This is in line with research that underscores the importance of training in reducing biases in AI(BAHUGUNA et al., 2023). The finding underscores the role of human oversight and understanding in AI applications.

H4: Data Quality & Diversity and AI Bias Supported by a path coefficient of -0.21 and a t-value of -3.01, H4 suggests that higher data quality and diversity are associated with lower AI bias. This resonates with the argument that diverse and high-quality data are crucial for unbiased AI outputs (Rehman et al., 2023). It highlights the need for robust data management practices.

H5: Regulatory Compliance and AI Bias H5 finds support with a path coefficient of 0.15 and a t-value of 2.18, indicating that regulatory compliance is positively associated with reduced AI bias. This aligns with studies emphasizing the role of regulations in guiding ethical AI use (Pandya et al., 2022). It suggests that adherence to regulatory standards is key in mitigating AI biases.

H6: Mediating Role of Organizational Culture The significant path coefficient (0.28) and t-value (4.02) for H6 support the mediating role of organizational culture in the relationship between AI integration and AI bias. This finding is consistent with literature that views organizational culture as a critical factor in technology adoption and its outcomes(Bagga et al., 2023). It implies that fostering an inclusive and ethics-focused culture is crucial for managing AI biases.

Implications of the Study

These findings have profound implications for practitioners and policymakers in the realm of AI and supply chain management. They underscore the need for diversified AI algorithms, comprehensive employee training, robust data management, and adherence to regulatory standards to mitigate AI biases. Moreover, they highlight the pivotal role of organizational culture in shaping the outcomes of AI integration. The study contributes to the growing body of knowledge on AI biases and offers practical insights for organizations striving to harness AI effectively and ethically.

6. Conclusions

The primary objective of this study was to delve into the intricate web of factors influencing AI bias in decision-making within the unique context of financial technology (FinTech)-based supply chain management, with a specific focus on Pakistan. In pursuit of this objective, a set of comprehensive hypotheses was formulated, grounded in existing theory and previous research, each aiming to explore the impact of various independent variables on the presence of AI bias. The study employed Structural Equation Modeling (SEM) through SmartPLS as the chosen methodology to rigorously analyze the collected data. The study engaged a diverse group of respondents, representing organizations actively involved in the FinTech and supply chain sectors in Pakistan.

The central problem addressed by this study was the need to understand the multifaceted relationship between AI integration, algorithm diversity, employee training, data quality, regulatory compliance, organizational culture, and AI bias in the decision-making processes within the evolving landscape of FinTech-based supply chain management.

Methodology and Respondents: The study employed Structural Equation Modeling (SEM) through SmartPLS as the chosen methodology, allowing for a comprehensive examination of the complex relationships between the variables. The respondents consisted of a diverse group of professionals from organizations engaged in FinTech and supply chain management within Pakistan. This diverse representation ensured a holistic perspective on the research problem.

Results and Key Findings: The study's results uncovered several key findings that significantly contribute to our understanding of AI bias in the context under investigation. Firstly, it revealed a positive correlation between the level of AI integration and AI bias, implying that organizations that extensively integrate AI into their operations may be more susceptible to biases in their decision-making processes.

Secondly, the research found that algorithm diversity plays a crucial role in mitigating AI bias. Organizations that utilize a variety of algorithms tend to experience lower levels of AI bias in their decision-making processes, emphasizing the importance of algorithm diversity in AI adoption.

Moreover, the study identified a significant relationship between employee training on AI and AI bias. Organizations with comprehensive employee training programs focused on AI tend to exhibit lower levels of bias in their decision-making processes, highlighting the importance of investing in employee training. Additionally, the study established a negative correlation between the quality and diversity of data used in AI systems and AI bias. Organizations that manage their data effectively, ensuring quality and diversity, tend to experience lower levels of AI bias in decision-making. Furthermore, the research revealed that higher regulatory compliance in AI usage is associated with a reduction in AI bias. This finding underscores the role of regulations in guiding ethical AI use and reducing bias in decision-making.

Lastly, the study unveiled an intriguing result: organizational culture mediates the relationship between AI integration and AI bias. This suggests that fostering an inclusive and ethics-focused organizational culture can mitigate the effects of AI bias, providing organizations with a means to counteract biases effectively.

The contribution of this study is multifaceted. It offers a comprehensive understanding of the factors influencing AI bias within FinTech-based supply chain management, providing insights into how these factors interact and collectively impact decision-making. This holistic perspective contributes to the literature on AI bias, which has often focused on individual elements in isolation.

Implications: The implications of this study extend to practical considerations. Organizations operating in the FinTech and supply chain sectors can use the insights gained from this research to make informed decisions regarding AI integration, algorithm diversity, employee training, data quality, and regulatory compliance. By addressing these aspects, they can strive for more equitable and ethical AI-driven decision-making processes.

Limitations and Future Studies: It is essential to acknowledge the limitations of this study. The research was conducted within the specific context of Pakistan's evolving FinTech sector, and the findings may not be directly transferable to other regions or industries. Additionally, the study relied on self-reported data from respondents, which can introduce response biases. Future studies may explore the specific types and manifestations of bias within the examined context and consider a broader range of industries and regions.

In conclusion, this study has provided a comprehensive examination of AI bias in FinTech-based supply chain management, offering valuable insights into the factors influencing bias and their interplay. The findings contribute to both academic knowledge and practical decision-making in the field of AI adoption. As organizations continue to embrace AI technologies, understanding and addressing biases become imperative for responsible and equitable business practices. This study represents a step forward in achieving that goal and paves the way for further research in the domain of AI ethics and decision-making.

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