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The impact of artificial intelligence on organizational decision-making processes

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Abstract: Using a mixed-methods approach, data was collected through quantitative surveys (N=258) and qualitative interviews with AI practitioners and decision-makers across multiple industries. Findings indicate that AI significantly improves decision efficiency by automating analytical tasks, reducing human cognitive biases, and enabling real-time insights. However, challenges persist, particularly in algorithmic transparency, ethical governance, and compliance with regulatory standards. Key findings reveal that AI integration positively influences decision effectiveness (β=0.156, p=0.031), but human oversight (β=0.381, p<0.001) and regulatory compliance (β=0.314, p<0.001) play crucial mediating roles. Ethical and security challenges necessitate stronger AI governance frameworks, as organizations struggle with bias mitigation, legal accountability, and AI explainability. Industry experts emphasize the need for a hybrid Human-AI collaboration model, ensuring AI remains an augmentation rather than a replacement for human decision-makers. This study contributes to AI governance literature by highlighting the importance of ethical AI deployment, transparent decision systems, and regulatory adherence. Future research should explore AI's impact in high-risk sectors, develop proactive AI compliance strategies, and examine cross-national AI regulatory frameworks to enhance responsible AI adoption globally.

Keywords: *Artificial intelligence, AI-driven decision-making, Ethical AI, Human oversight, Organizational strategy, Regulatory compliance.*

1. Introduction

Artificial Intelligence (AI) has become a transformative force in modern organizational decision-making. By enhancing predictive capabilities, processing vast amounts of data in real time, and minimizing human cognitive biases, AI provides organizations with strategic advantages [1, 2]. In particular, AI supports more accurate forecasting, faster operational decisions, and automation of complex analytical tasks. However, with these opportunities come challenges—especially regarding ethical concerns, data privacy, algorithmic transparency, and the need for human oversight [3, 4].

AI has fundamentally changed the landscape of organizational decision-making by enhancing efficiency, predictive capabilities, and data-driven insights. However, challenges such as bias, ethical concerns, and the need for human oversight must be addressed to maximize AI's potential. As AI technology advances, organizations must adopt responsible AI governance frameworks to ensure that AI-driven decision-making aligns with ethical standards and organizational goals. Future research should explore how AI can further optimize decision-making while mitigating its risks.

The based on the background of the study is that 1) to analyze the historical evolution of decision-making processes in organizations and the role of AI in transforming these processes. 2) to examine how AI-driven decision-making improves efficiency, accuracy, and predictive capabilities in

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organizational decision-making. 3) to identify and evaluate the challenges, including ethical concerns, biases, and security risks, in AI-assisted decision-making.

The proposed research framework provides the relationship between AI's influence on organizational decision-making and the effectiveness of AI-driven decision-making, while considering the moderating effects of human oversight and regulatory compliance. The conceptual framework shows as Figure 1.1.

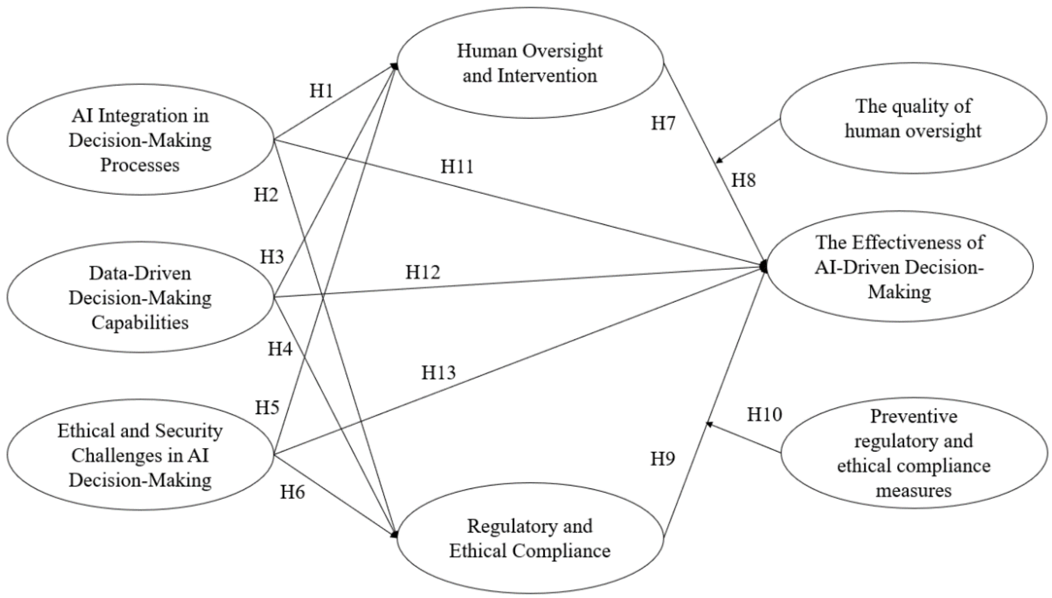

Figure 1.
The research framework.

2. Research Methodology

Due to the complex interplay between AI and decision-making process, it is challenging to find direct, effective, and comprehensive statistical indicators that serve as proxy variables.

2.1. Research Design

This study adopts a mixed-method research design, combining quantitative surveys and qualitative interviews to capture both statistical trends and in-depth insights from AI users and decision-makers. The quantitative approach is used to measure the relationships among key variables, including AI integration, data-driven decision-making capabilities, ethical and security challenges, human oversight, regulatory compliance, and decision-making effectiveness. Meanwhile, the qualitative approach involves semi-structured interviews with industry professionals to provide contextual depth and a deeper understanding of AI adoption challenges. The integration of quantitative and qualitative methods allows for a more nuanced understanding of AI-driven decision-making.

In summary, the mixed-methods approach strengthens research reliability, ensures balanced data interpretation, and enhances the practical applicability of AI-driven decision-making findings. This combination of quantitative rigor and qualitative depth makes the study more robust, actionable, and relevant to both researchers and industry practitioners.

2.2. Population and Samples size

The target population for this study consists of business professionals, AI practitioners, and decision-makers operating in industries that have actively integrated Artificial Intelligence (AI)

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technologies into their business intelligence, decision-support systems, operational automation, and strategic planning. The study focuses on enterprises in the Yangtze River Economic Belt, a major economic hub that includes Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Chongqing, Sichuan, Guizhou, and Yunnan.

To ensure a balanced and representative sample, the study selects ten leading enterprises from the Yangtze River Economic Belt based on the following criteria: 1) AI Adoption Level. Each selected enterprise has implemented AI-driven systems, such as machine learning models, predictive analytics, or AI-based automation, 2) Industry Diversity. Organizations from multiple industries are selected to examine AI's role across different sectors, 3) Company Size Variation. A mix of large corporations and mid-sized enterprises is included to explore AI adoption at different scales, 4) Geographical Distribution. Companies from multiple provinces within the Yangtze River Economic Belt are chosen to ensure regional representation, and 5) Regulatory Compliance. Enterprises are selected based on their adherence to both Chinese AI governance frameworks and international AI ethics guidelines.

The sample size was calculated according to Yamane [5] to ensure statistical validity and meaningful insights, the study adopts the following sample size approach:

1) 258 respondents for the quantitative survey, including business leaders, AI practitioners, and decision-makers across various industries.

2) 10 participants for qualitative interviews, selected based on their expertise in AI adoption, strategic decision-making, and regulatory compliance.

The selected sample size aligns with business research standards and ensures that the study captures both broad industry trends (quantitative data) and in-depth insights (qualitative interviews). This approach enhances the reliability and applicability of the findings to real-world AI decision-making scenarios.

2.3. Research Hypothesis

H_1: The higher the degree of AI integration in decision-making, the greater the need for human oversight and intervention.

H_2: The higher the degree of AI integration in decision-making, the stricter the regulatory and ethical compliance requirements.

H_3: The stronger the data-driven decision-making capability, the shift in human oversight and intervention from direct control to strategic guidance.

H_4: The stronger the data-driven decision-making capability, the lower the difficulty of implementing regulatory and ethical compliance.

H_5: The more complex the ethical and security challenges, the higher the necessity for human oversight and intervention.

H_6: The more significant the ethical and security challenges, the greater the importance of regulatory and ethical compliance.

H_7: Appropriate human oversight and intervention are positively correlated with the effectiveness of AI-driven decision-making.

H_8: The quality (rather than quantity) of human oversight is positively correlated with the effectiveness of AI-driven decision-making.

H_9: A well-established regulatory and ethical compliance framework is positively correlated with the long-term effectiveness of AI-driven decision-making.

H_{10}: Preventive regulatory and ethical compliance measures have a more positive impact on the effectiveness of AI-driven decision-making than reactive measures.

H_{11}: The degree of AI integration in decision-making is positively correlated with the effectiveness of AI-driven decision-making, but this relationship is mediated by the quality of human oversight.

H_{12}: Data-driven decision-making capability is positively correlated with the effectiveness of AI-driven decision-making, with this relationship partially mediated by the level of regulatory and ethical compliance.

H_{13}: The ability to manage ethical and security challenges is positively correlated with the effectiveness of AI-driven decision-making.

3. Results of Analysis

The data analysis process in this study employs both quantitative and qualitative methods to ensure a comprehensive understanding of AI-driven decision-making. The analysis follows a systematic approach, including data preparation, statistical techniques, thematic analysis, and interpretation to address the research objectives.

3.1. Expected Findings from Quantitative Data Analysis

To examine statistical relationships between AI integration, decision-making capabilities, ethical challenges, human oversight, regulatory compliance, and AI effectiveness, there is the expected findings from quantitative data analysis.

3.1.1. Sample Distribution

The sample distribution provides a detailed overview of the demographics, industry representation, AI adoption levels, and AI usage frequency among the study participants. By analyzing these factors, the study ensures a diverse representation across industries and organizational levels, allowing for a comprehensive evaluation of AI-driven decision-making effectiveness. The distribution of participants helps to assess the extent of AI adoption and the challenges faced by different industries in implementing AI technologies for decision-making processes. The details show as Table 4.

Table 4.
Basic information from sample groups.

Items	**Options**	**Frequency**	**Percentage (%)**	**Cumulative percentage (%)**
Industry	Technology	130	50.39	50.39
	Finance	42	16.28	66.67
	Healthcare	37	14.34	81.01
	Education	20	7.75	88.76
	Retail	16	6.20	94.96
	Manufacturing	13	5.04	100.00
Job role	Executive/Manager	83	32.17	32.17
	AI/Data Analyst	83	32.17	64.34
	IT Specialist	60	23.26	87.60
	Decision-Maker	32	12.40	100.00
How long has your organization used AI in decision-making	Less than 1 year	51	19.77	19.77
	1-3 years	97	37.60	57.36
	4-6 years	93	36.05	93.41
	More than 6 years	17	6.59	100.00
How frequently does your organization use AI for decision-making	Rarely	26	10.08	10.08
	Occasionally	68	26.36	36.43
	Frequently	108	41.86	78.29
	Always	56	21.71	100.00
Total		258	100.0	100.0

Table 4 provides an overview of the demographic distribution of the study's sample group, including industry type, job roles, AI usage experience, and frequency of AI utilization in decision-making. The sample consists of 258 respondents from various industries and organizational roles, ensuring a diverse and representative dataset.

The findings indicate that AI is widely adopted in technology, finance, and healthcare sectors, with executives and AI specialists playing a crucial role in decision-making. While most organizations have 1-6 years of AI adoption experience, there is still a variation in how frequently AI is utilized. The results highlight a strong trend toward AI-driven decision-making but also suggest that certain industries and roles are lagging in full-scale AI integration.

3.1.2. Correlation Analysis

Correlation analysis is conducted to examine the relationships between key research variables, including AI integration, data-driven decision-making capabilities, ethical and security challenges, human oversight, regulatory compliance, and AI-driven decision-making effectiveness. The goal is to determine whether these variables are significantly related and how they influence one another.

Pearson's correlation coefficient (r) is used as the primary statistical measure to assess the strength and direction of relationships between variables. A positive correlation ($r > 0$) indicates that as one variable increases, the other also increases, while a negative correlation ($r < 0$) suggests an inverse relationship. A correlation coefficient close to zero implies little to no relationship between the variables. The Pearson correlation for analysis in this research shown as Table 4.2.

Table 5.
Pearson Correlation for analysis.

Pearson correlation								
	Mean	**S.D.**	**DMP**	**DMC**	**ESC**	**HOI**	**REC**	**AIE**
DMP	3.271	1.149	1					
DMC	3.284	1.148	0.670**	1				
ESC	3.233	1.194	0.702**	0.730**	1			
HOI	3.235	1.149	0.699**	0.684**	0.685**	1		
REC	3.233	1.135	0.689**	0.654**	0.725**	0.717**	1	
AIE	3.266	1.105	0.726**	0.709**	0.708**	0.781**	0.761**	1

Note: * $p<0.05$ ** $p<0.01$
DMP: AI Integration in Decision-Making Processes
DMC: Data-Driven Decision-Making Capabilities
ESC: Ethical and Security Challenges in AI Decision-Making
HOI: Human Oversight and Intervention
REC: Regulatory and Ethical Compliance
AIE: The Effectiveness of AI-Driven Decision-Making

Table 5 presents the Pearson correlation matrix for the key variables in this study, examining the relationships between AI integration in decision-making processes (DMP), data-driven decision-making capabilities (DMC), ethical and security challenges (ESC), human oversight and intervention (HOI), regulatory and ethical compliance (REC), and AI-driven decision-making effectiveness (AIE).

The mean values of the variables range from 3.233 to 3.284, with standard deviations between 1.105 and 1.194. These values suggest that participants' responses were fairly distributed but varied moderately across different constructs.

Overall, the correlation analysis supports the study's hypothesis that AI-driven decision-making effectiveness is influenced by AI integration, data capabilities, human oversight, and compliance frameworks. These findings lay the groundwork for further regression and structural equation modeling (SEM) analysis to validate causal relationships.

3.1.3. Regression Analysis

To examine the influence of the three independent variables—AI Integration in Decision-Making Processes (DMP), Data-Driven Decision-Making Capabilities (DMC), and Ethical and Security Challenges (ESC)—on Human Oversight and Intervention (HOI), a multiple regression analysis was conducted. The results indicate that the overall regression model is significant ($F = 124.319$, $p < 0.001$), with an adjusted R^2 of 0.590, suggesting that these three independent variables collectively explain 59.0% of the variance in Human Oversight and Intervention, which is a substantial explanatory power.

The findings shown in Table 6 reveal that all three independent variables have a significant positive impact on Human Oversight and Intervention.

Table 6.
Linear regression analysis results: The Impact of Independent Variables on Human Oversight and Intervention.
(n=258)

	Unstandardized coefficients		**Standardized coefficient**	***t***	***p***	**Collinearity diagnostics**	
	B	**Standard error**	***Beta***			**VIF**	**Tolerance**
Constant	0.450	0.152	-	2.970	0.003**	-	-
AI Integration in Decision-Making Processes	0.343	0.059	0.343	5.795	0.000**	2.203	0.454
Data-Driven Decision-Making Capabilities	0.278	0.062	0.278	4.491	0.000**	2.394	0.418
Ethical and Security Challenges in AI Decision-Making	0.232	0.062	0.241	3.743	0.000**	2.601	0.384
R^2	0.595						
Adjusted R^2	0.590						
F	$F=124.31$, $p=0.000$						
D-W Value	2.373						
Note: Dependent Variable = Human Oversight and Intervention							
* $p<0.05$ ** $p<0.01$							

Table 6 presents the linear regression analysis results, examining the impact of AI integration in decision-making processes, data-driven decision-making capabilities, and ethical and security challenges in AI decision-making on human oversight and intervention.

The findings shown in Table 7 reveal that the Combined Impact of Independent and Mediating Variables on the Effectiveness of AI-Driven Decision-Making.

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Table 7.
Linear regression analysis results.
(n=258)

	Unstandardized coefficients		Standardized coefficient	*t*	*p*	Collinearity diagnostics	
	B	**Standard error**	***Beta***			**VIF**	**Tolerance**
Constant	0.214	0.123	-	1.741	0.083	-	-
AI Integration in Decision-Making Processes	0.162	0.051	0.169	3.210	0.001**	2.603	0.384
Data-Driven Decision-Making Capabilities	0.149	0.051	0.155	2.951	0.003**	2.602	0.384
Ethical and Security Challenges in AI Decision-Making	0.055	0.052	0.060	1.053	0.293	3.022	0.331
Human Oversight and Intervention	0.312	0.052	0.325	6.029	0.000**	2.729	0.366
Regulatory and Ethical Compliance	0.260	0.053	0.268	4.933	0.000**	2.768	0.361
R^2	0.732						
Adjusted R^2	0.727						
F	$F(5,252)=137.822$, p=0.000						
D-W Value	2.094						

Note: Dependent Variable = Human Oversight and Intervention
* $p<0.05$ ** $p<0.01$

Table 7 presents the linear regression analysis results, evaluating the impact of AI integration in decision-making, data-driven decision-making capabilities, ethical and security challenges, human oversight and intervention, and regulatory and ethical compliance on the effectiveness of AI-driven decision-making.

The regression analysis confirms that human oversight and regulatory compliance play the most critical role in ensuring AI-driven decision-making effectiveness. While AI integration and data-driven decision-making contribute directly, ethical and security challenges primarily exert an indirect effect via compliance and oversight mechanisms. These findings emphasize that effective AI decision-making requires not only advanced technology but also strong governance frameworks and human supervision.

3.1.4. Confirmatory Factor Analysis (CFA)

This study's measurement model consists of six latent variables, each measured by six observed indicators:

1) AI Integration in Decision-Making Processes (DMP)
2) Data-Driven Decision-Making Capabilities (DMC)
3) Ethical and Security Challenges (ESC)
4) Human Oversight and Intervention (HOI)
5) Regulatory and Ethical Compliance (REC)
6) Effectiveness of AI-Driven Decision-Making (AIE)

The CFA results, as illustrated in the structural path diagram, indicate the measurement model's robustness in capturing the relationships between observed variables (measurement items) and their respective latent constructs. The model includes six latent variables shown as Figure 2:

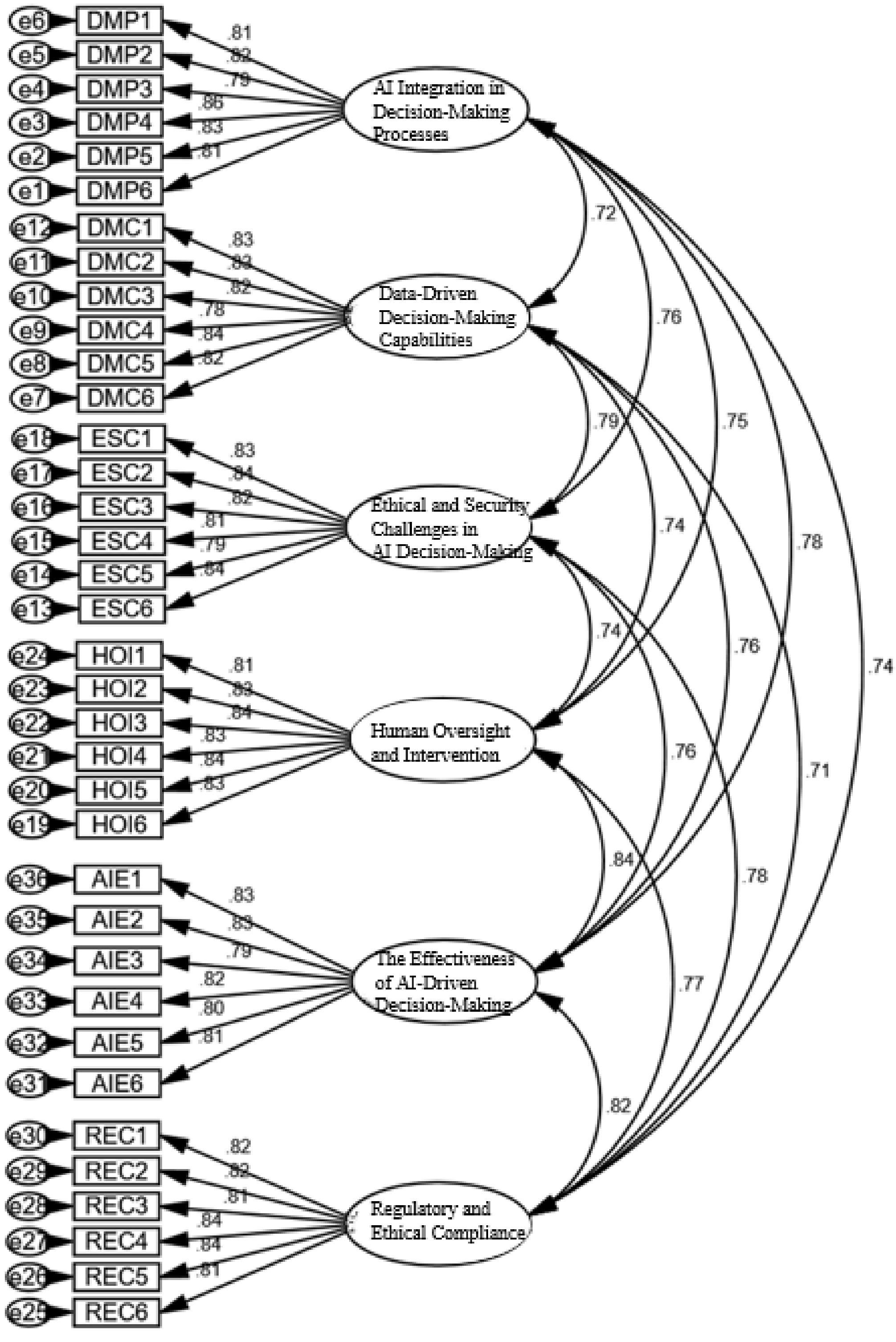

Figure 2.
The structural path diagram of CFA.

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The CFA from Table 2 results confirm that AI-driven decision-making is most effective when supported by human oversight and strong ethical compliance frameworks. The model validates that data-driven AI and ethical security considerations play a crucial role, but their impact is amplified when coupled with human supervision and regulatory policies.

To assess the measurement model's goodness-of-fit, multiple fit indices were examined [6] shown as Table 8:

Table 8.
The measurement model's goodness-of-fit.

Fit Index	Recommended Threshold	CFA Model Result
Chi-square/df (χ^2/df)	< 3.0	2.634
Comparative Fit Index (CFI)	> 0.90	0.942
Tucker-Lewis Index (TLI)	> 0.90	0.937
Root Mean Square Error of Approximation (RMSEA)	< 0.08	0.058
Standardized Root Mean Square Residual (SRMR)	< 0.08	0.041

Table 8 presents the measurement model's goodness-of-fit using multiple fit indices to assess the Confirmatory Factor Analysis (CFA) model's validity. These indices determine whether the hypothesized model fits the collected data appropriately.

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Table 9.
The convergent validity and internal consistency reliability of the measurement model.

Variables	Test Items	Standard load factor	SMC	AVE	CR
DMP	DMP1	0.812	0.660	0.671	0.925
	DMP2	0.821	0.674		
	DMP3	0.790	0.624		
	DMP4	0.857	0.735		
	DMP5	0.825	0.681		
	DMP6	0.809	0.654		
DMC	DMC1	0.827	0.684	0.670	0.924
	DMC2	0.828	0.685		
	DMC3	0.825	0.680		
	DMC4	0.778	0.605		
	DMC5	0.835	0.697		
	DMC6	0.818	0.669		
ESC	ESC1	0.833	0.694	0.676	0.926
	ESC2	0.836	0.699		
	ESC3	0.822	0.675		
	ESC4	0.813	0.661		
	ESC5	0.791	0.625		
	ESC6	0.838	0.702		
HOI	HOI1	0.810	0.656	0.691	0.931
	HOI2	0.829	0.688		
	HOI3	0.840	0.705		
	HOI4	0.833	0.694		
	HOI5	0.840	0.706		
	HOI6	0.834	0.696		
REC	REC1	0.819	0.671	0.675	0.926
	REC2	0.820	0.672		
	REC3	0.812	0.660		
	REC4	0.835	0.698		
	REC5	0.835	0.697		
	REC6	0.806	0.650		
AIE	AIE1	0.834	0.695	0.664	0.922
	AIE2	0.831	0.691		
	AIE3	0.789	0.623		
	AIE4	0.823	0.678		
	AIE5	0.800	0.639		
	AIE6	0.810	0.656		

Table 9 evaluates convergent validity and internal consistency reliability for six constructs using Standardized Loadings, Squared Multiple Correlation (SMC), Average Variance Extracted (AVE), and Composite Reliability (CR). All standardized factor loadings exceed 0.70, confirming strong indicator reliability. AVE values surpass 0.50, indicating adequate convergent validity. CR values exceed 0.90, establishing strong internal consistency reliability.

Table 10.
Pearson Correlation and AVE Square Root Values.

	DMP	**DMC**	**ESC**	**HOI**	**REC**	**AIE**
DMP	0.819					
DMC	0.670	0.819				
ESC	0.702	0.730	0.822			
HOI	0.699	0.684	0.685	0.831		
REC	0.689	0.654	0.725	0.717	0.821	
AIE	0.726	0.709	0.708	0.781	0.761	0.815

Table 10 presents the Pearson correlation coefficients between constructs alongside the square root values of the Average Variance Extracted (AVE) for each construct. This table serves as an assessment of discriminant validity, following the Fornell-Larcker criterion [7]. Each construct has sufficient discriminant validity, meaning that the measurement items uniquely capture their intended constructs. All constructs are significantly correlated, supporting their relevance to the research model. The strong relationship between human oversight (HOI), regulatory compliance (REC), and AI-driven decision effectiveness (AIE) confirms the importance of governance mechanisms in ensuring AI's effectiveness in decision-making.

3.1.5. Structural Equation Modeling (SEM)

By using SEM, this study provides a more comprehensive validation of the hypothesized relationships, considering both direct and indirect effects of AI-driven decision-making. This approach allows for a deeper understanding of how AI adoption impacts organizational decision-making effectiveness through governance, compliance, and ethical considerations. Figure 3 shows the SEM framework.

AI Integration and Data-Driven Decision-Making Capabilities positively impact AI-driven decision effectiveness, both directly and indirectly. Ethical and Security Challenges influence AI decision-making through governance mechanisms like human oversight and regulatory compliance. Human Oversight and Regulatory Compliance are significant mediators, confirming that AI alone is insufficient for effective decision-making without appropriate oversight.

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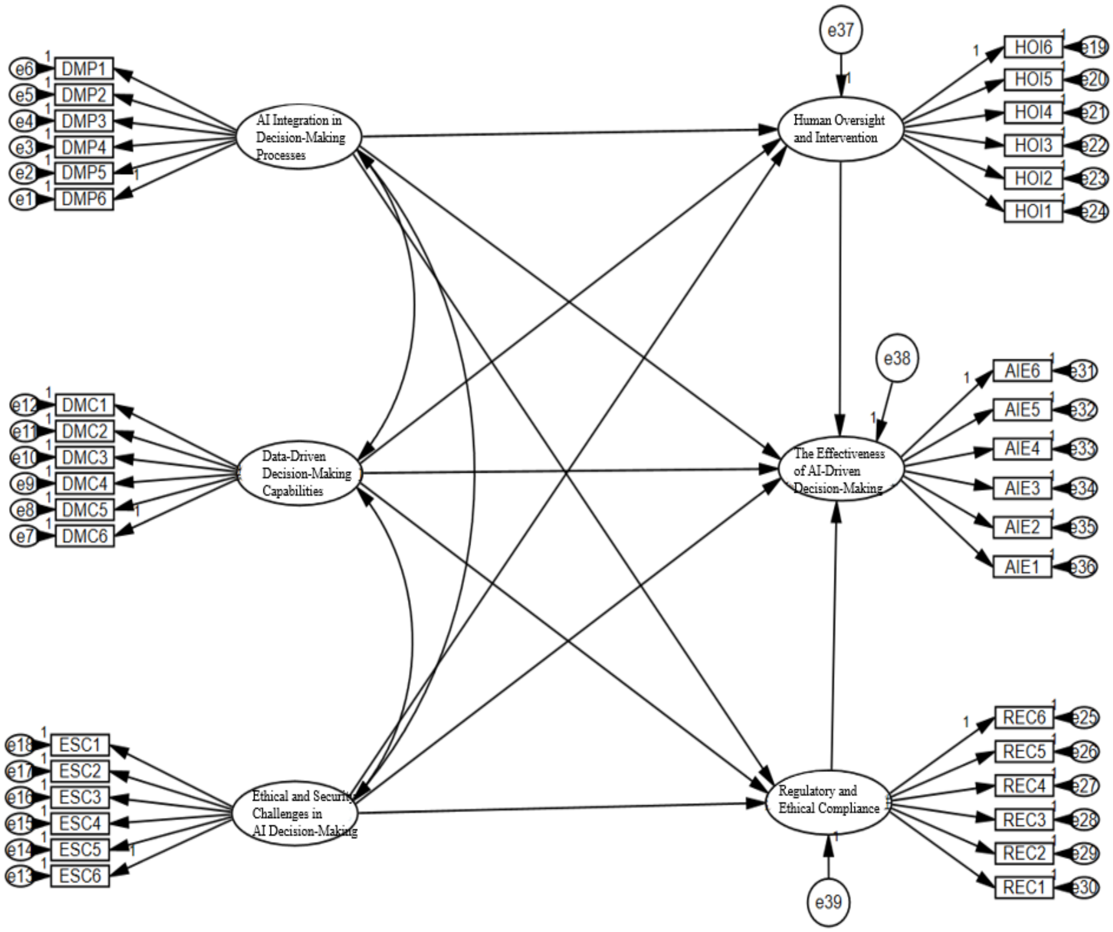

Table 3.
Structural Equation Modeling (SEM).

Thus, the Structural Equation Model (SEM) is validated and well-fitted to the data, supporting further analysis of path relationships.

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Table 11.
Path Analysis and Hypothesis Testing

X (Independent Variable)	→	Y (Dependent Variable)	Unstandardized Path Coefficient	S.E.	C.R.	P	Standardized Path Coefficient
AI Integration in Decision-Making Processes	→	Human Oversight and Intervention	0.374	0.078	4.823	***	0.374
Ethical and Security Challenges	→	Regulatory and Ethical Compliance	0.382	0.078	4.916	***	0.443
Data-Driven Decision-Making Capabilities	→	Human Oversight and Intervention	0.265	0.081	3.270	0.001	0.268
Data-Driven Decision-Making Capabilities	→	Regulatory and Ethical Compliance	0.121	0.077	1.580	0.114	0.128
Ethical and Security Challenges	→	Human Oversight and Intervention	0.226	0.078	2.884	0.004	0.252
AI Integration in Decision-Making Processes	→	Regulatory and Ethical Compliance	0.310	0.074	4.200	***	0.323
AI Integration in Decision-Making Processes	→	Effectiveness of AI-Driven Decision-Making	0.148	0.069	2.156	0.031	0.156
Data-Driven Decision-Making Capabilities	→	Effectiveness of AI-Driven Decision-Making	0.143	0.066	2.178	0.029	0.154
Ethical and Security Challenges	→	Effectiveness of AI-Driven Decision-Making	0.002	0.069	0.033	0.974	0.003
Human Oversight and Intervention	→	Effectiveness of AI-Driven Decision-Making	0.359	0.067	5.358	***	0.381
Regulatory and Ethical Compliance	→	Effectiveness of AI-Driven Decision-Making	0.308	0.071	4.337	***	0.314

Table 11 presents path analysis results, which test the relationships between independent variables (X), dependent variables (Y), and mediating variables using structural equation modeling (SEM). The analysis includes unstandardized and standardized path coefficients, standard errors, critical ratios (C.R.), and significance levels. The hypotheses supporting AI governance (HITL model) and AI ethics frameworks were strongly validated by these findings.

3.2. Expected Findings from Qualitative Data Analysis

The qualitative data analysis is expected to provide deeper insights into the role of AI in organizational decision-making beyond statistical correlations. By analyzing interviews with executives, AI practitioners, and decision-makers, key themes related to AI integration, human oversight, and regulatory challenges will emerge. These qualitative findings will complement the quantitative results, ensuring a holistic understanding of AI's impact on decision-making processes.

One of the anticipated findings is that AI is fundamentally reshaping how organizations approach decision-making by enhancing efficiency, reducing human biases, and enabling data-driven insights. However, qualitative responses may reveal that while AI adoption improves decision accuracy, concerns regarding ethical implications, human oversight, and compliance challenges persist. Many executives are likely to highlight organizational resistance, skill gaps, and AI's interpretability issues as barriers to full-scale adoption.

Moreover, AI practitioners may emphasize the need for a balanced approach, ensuring AI-assisted decisions incorporate human intuition and ethical considerations. Discussions on AI transparency and explainability will likely emerge as recurring concerns, supporting the view that decision-makers must understand AI-generated insights rather than blindly trusting algorithms. Finally, interviews are expected to show that AI effectiveness varies across industries, with sectors such as finance, healthcare, and manufacturing experiencing different levels of AI-driven transformation.

4. Conclusion

Artificial Intelligence (AI) significantly enhances organizational decision-making by improving efficiency, speed, and analytical capacity. It supports real-time insights, automation of repetitive tasks, and predictive accuracy. However, these benefits must be balanced with risks involving fairness, accountability, and social impact.

According to Dignum [8] AI systems must be developed with embedded ethical reasoning and human-centric values, which go beyond technical performance. This aligns with the call for value-sensitive design to ensure AI not only operates efficiently but also respects societal norms and user expectations [9]. Thus, organizations must implement transparent, explainable AI governance models and foster a culture of responsible innovation.

Ultimately, effective AI-driven decision-making should be seen as a collaborative human-AI process. By embracing both technological advancements and ethical foresight, organizations can leverage AI to make strategic decisions while maintaining public trust and social legitimacy.

5. Recommendation

To advance responsible AI implementation, organizations should foster interdisciplinary collaboration among data scientists, ethicists, and policymakers. Investing in AI literacy and ethics training is essential for equipping decision-makers with critical understanding [10]. Moreover, governments should establish dynamic, sector-specific AI regulatory frameworks to ensure adaptability in fast-evolving industries [11]. Cross-sector partnerships and international dialogue will be key in promoting transparency, fairness, and inclusiveness in AI-driven organizational decision-making.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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