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Research Article

AI Usage Intensity and Organizational Performance: The Mediating Effect of Decision Quality and the Moderating Effect of AI Trust

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Abstract: **Purpose:** This research seeks to analyse the effect of the intensity of AI application on organizational performance via decision quality. Furthermore, this research explores the effect of AI trust (AI literacy) as a moderator variable in the proposed relationship. **Methodology Employed:** Quantitative and cross-sectional research design was used where survey responses were gathered from employees working in the IT and ITES industries. The proposed hypotheses were examined using the moderated mediation approach (PROCESS Model 7). **Key Findings:** It is evident that AI application has a significant effect on decision quality and organization performance. Nevertheless, there is a negative moderating effect when there is high AI trust on decision quality and organizational performance. **Managerial Implications:** Organisations must concentrate on developing decision-making skills and competencies instead of emphasizing artificial intelligence implementation. The use of artificial intelligence requires managers to balance AI through critical reflection. Artificial intelligence education and AI transparency would help improve human-AI interaction. **Contribution of the Study:** The proposed model offers an interesting contribution by considering decision quality as a mediator between artificial intelligence usage and organisational performance. Furthermore, it considers the role of artificial intelligence trust as a boundary condition, which makes the model more practical and realistic.

Keywords: AI Usage Intensity, Trust in Ai Tools, Decision Quality, Organisational Performance, Moderated Mediation

INTRODUCTION

From being an experimental technology, artificial intelligence (AI) has moved quite fast to become a core part of the work system of an organisation, changing how things are done within it. AI technologies are now increasingly being used by contemporary organisations in order to boost their efficiency and effectiveness, as well as help them make better decisions. Empirical studies have proven that through the use of AI, people's analysis skills are enhanced and they are able to make quicker and more efficient decisions [1-3]. In addition, organizations that have embraced AI technologies have reported increases in productivity and efficiency due to intensive AI utilisation [4-5].

Even as such developments continue, the association between the use of artificial intelligence and organizational performance is not straightforward. Recent evidence suggests that the adoption of AI may not necessarily lead to better decision-making processes and performance because a paradox has emerged where the adoption of AI tools does not always result in better decision-making or performance [6,7]. In some cases, workers depend on the information generated by AI tools without adequate evaluation, causing bad decisions. The emergence of this problem suggests a bigger concern that although AI tools can provide complex analysis, their effectiveness will depend on how people use their results. On the other hand, recent studies show that the efficiency of AI-based decisions is moderated by a set of critical boundary conditions, including AI trust and AI literacy. The level of trust toward artificial intelligence is a crucial criterion for accepting the algorithmic suggestions provided. Although moderate trust is beneficial for acceptance and productive utilization, extreme trust may cause automation bias, meaning that people will over-trust the AI output and put less effort into analysing information critically [8,9]. In this case, the quality of decisions may be compromised, resulting in lower benefits of implementing artificial intelligence. At the same time, low AI trust may also negatively impact adoption and utilization, which will prevent companies from capitalizing on the AI potential.

At the same time, AI literacy has become anFother vital competence that can determine the way people relate to AI systems. It involves the ability of an individual to comprehend, analyse, and critique the results produced by AI technologies. Those employees who have greater AI literacy skills can use insights provided by AI technologies in combination with their competencies, thus making decisions that are more balanced [10,11]. Additionally, the development of AI literacy can improve users’ confidence and reduce their uncertainty when interacting with AI, thus increasing the effectiveness of using this technology [12]. Conversely, insufficient AI literacy can lead to the wrong use, understanding, or application of AI technology, resulting in poor decision-making practices.

In theory, this study draws upon several frameworks. The TAM and its variants emphasise the role played by users’ perceptions, including trust and perceived usefulness, in shaping usage behaviour [13]. Trust in automation, on the other hand, further explains how people balance their trust in intelligent systems, noting that over trust and mistrust may lead to suboptimal decision making [8]. Social cognitive theory, on the other hand, draws attention to the importance of individual competencies, including AI literacy, in driving outcomes [14]. In a strategic sense, the RBV provides insights into how organizations can utilise AI as a valuable resource. Under this framework, effective utilisation requires the presence of complementary human skills [5].

It is against this background that the current research contributes to existing literature by introducing an integrated concept of moderated mediation. Namely, the paper will focus on the effects of intensity of AI utilization on organizational performance via decision quality with a view to moderating the effect using the levels of AI trust and literacy. The study goes further than the existing literature by avoiding oversimplification and taking into account that AI provides value in organizations depending on how users interpret and use the insights it provides. Overall, the study makes a contribution to the new line of inquiry in the field by emphasizing the conditional role of AI usage intensity when predicting organizational performance. In other words, even though the use of AI positively impacts the level of organizational performance, its effectiveness relies on the decisions that individuals make on the basis of AI insights. This is why, along with mediation, the study will focus on moderation and examine the impact of AI trust and AI literacy on organizational performance (Table 1).

However, previous studies have concentrated primarily on the direct effects of AI use on performance [4,5] while neglecting the role of moderation in influencing decision-making processes for gaining such advantages [15]. Besides, critical factors including AI trust and AI literacy have received separate consideration in previous research [8,10] with limited efforts towards integrating these aspects into a holistic moderated mediation model.

In order to structure the empirical analysis, the following research questions are developed from the theoretical model, focusing on how AI usage impacts organizational performance via decision quality, as well as the conditions for this effect.

Table 1: Research Gap

Factor	Existing body of knowledge	Unaccounted factors
AI usage → Performance	Widely documented: The degree of integration of the AI system within the task procedures of the workers, leading to more efficient processing, better decision support, and higher productivity, is known as AI usage intensity [4-6].	Fails to account the underlying process
Decision Making Role	Decision-making is the central point of the relationship between technology and performance, and effective and timely decision-making based on proper information ensures efficient resource utilisation and improved performance [5,15].	Occasionally examined as an intervening variable
Trust in AI	Trust in AI has an important role in influencing the manner in which people will deal with AI systems, considering that it will affect the level at which they will depend on AI-generated information; however, trust can result in over-dependence on AI-generated information [8,9,16].	Not embedded into process framework
AI literacy	AI literacy is essential for influencing the interaction between people and AI technologies because it indicates that people will be able to comprehend and evaluate AI-generated information effectively [10-12].	Never accounted as a moderator
Combined Moderated mediation model	The majority of studies have considered the effect of the use of AI on performance with scant consideration being paid to how these relationships were achieved [4-5]. In addition, decision quality is seldom used as an intervening variable, while important human factors like AI trust and AI literacy are separately considered in most cases [8,15].	No integrated model that captures both process and boundary variables exists.

- **RQ1:** How does AI usage intensity in the organisation by the employees enhance the firm or organisational performance through decision quality
- **RQ2:** How do proposed moderator (Trust in AI) moderates the relationship between focal predictor AI usage intensity and the mediating variable (decision quality) thereby, its indirect effect on firm or organisational performance

The current paper is divided into several sections that have the following structure. First, there will be an introduction of the research problem, discussion of the research context, formulation of research questions. In the second part, there will be a review of literature and development of the theoretical framework and hypotheses. Third, the methodological issues will be addressed research design, data gathering process, construct measurement and analytical methods will be discussed. Fourth, empirical findings will be presented. Fifth, conclusions will be made based on the findings' discussion within the existing body of knowledge.

Literature Review

The proposed moderated mediation relationship can best be explained from the point of view of the automation-augmentation perspective and resource-based view (RBV). According to the automation-augmentation perspective, the role of AI is not substitutional but rather enhancing the cognitive abilities of people due to making decisions faster and based on more reliable information [2,3]. As for organizations, the effectiveness of their decision-making is likely the primary factor determining their performance, as well as one of the mechanisms through which the benefits of AI technology can be leveraged. From an RBV standpoint, AI constitutes a valuable resource that cannot deliver its full potential unless used with the help of organizational capabilities [5]. Among such capabilities is decision quality that affects task completion and organizational performance positively [15]. It can thus be concluded that a higher intensity of AI usage contributes to better decision quality resulting in organizational success. Nevertheless, the efficiency of AI-powered decision making is subject to individual interactions with AI tools. From the perspective of trust in automation theory, trust affects the degree to which people depend on AI-generated information [8]. As such, appropriate trust contributes to efficient AI usage, while too much trust may cause automation bias, leading to less critical thinking and poor decision outcomes [9]. Likewise, social cognitive theory suggests that people's abilities to use technology efficiently depend on their skills, including AI literacy [14]. People with higher AI literacy tend to analyse AI-generated information, while those with lower AI literacy might abuse the tool [10]. Therefore, AI trust/AI literacy can be considered a boundary condition that determines the strength of the relationship between AI usage and decision quality and, therefore, the impact of the latter on performance.

Intensity of the use of artificial intelligence is based on how well employees incorporate the use of AI in their tasks. Within the automation-augmentation framework, AI improves human cognitive ability through quicker analysis of vast datasets and evidence, resulting in more accurate and reliable decisions [2,3]. Previous literature suggests that systems enabled by AI allow individuals to overcome information-processing limitations and support the process of evidence-based decision making, which results in superior-quality decisions [15,17]. Additionally, AI can decrease the occurrence of human bias, allowing for objective and quicker decision making [5,7]. Therefore, high intensity of AI use should increase decision quality.

H1

There is a significant and positive relationship between AI usage intensity and decision quality in the organisations.

The decision quality represents the level of correctness, timeliness, and accessibility of information used for making decisions. The decision quality is among those essential aspects that have a significant influence on the success of companies. High-quality decisions that are made basing on analysed information enable organizations to attain the best usage and reaction, which result in outstanding organizational performance [15,17]. The decision quality guarantees the absence of mistakes, efficiency, and effective accomplishment of tasks, which contributes to better organizational performance [7]. In addition, the quality decisions that are made according to outstanding analytical skills ensure long-term outcomes [2,5]. Hence it is logical to expect that enhanced decision quality by employees would lead to more robust organisational or firm performance.

H2

There is a significant and positive relationship between decision quality and Firm or organisational performance.

The intensity of AI use is determined by the degree of dependence of employees on artificial intelligence tools while performing their job responsibilities. With AI integration into critical business operations, companies have been able to increase their efficiency, perform automated activities, and make informed decisions at a much faster pace. It has been found through recent researches that adoption of AI leads to an increase in productivity and efficiency due to the effective usage of information [4,6] In addition, the use of AI helps organizations in responding promptly to changing situations, which leads to performance improvements [1,3].

H3

There is a positive and significant relationship between the intensity of AI usage and organizational or firm performance.

The effectiveness of AI utilization as an aid to enhance the quality of decisions is not only determined by the amount used but also by individuals' perception and interaction with the AI systems. Based on the theories of trust in automation, the role of AI trust is important for determining the extent to which individuals utilize and adopt AI recommendations recommendations [8]. Though having enough trust will assist in the effective utilization of AI systems, too much trust might have negative impacts on decision-making processes. Too little trust, on the other hand, might lead to ineffective use of the AI system. Another concept worth mentioning in relation to the effectiveness of AI as a means of improving decision quality is AI literacy. According to Ng *et al*. [11], Long and Magerko [10] the degree of AI literacy in an individual determines his or her engagement with AI technology. On the other hand, individuals who have low AI literacy may fail to make good use of AI and improve their decisions. Therefore, it can be seen that both AI trust and AI literacy moderate the effect of AI usage on decision quality in terms of its varying effect at different levels of the moderator.

H4

AI trust (or AI literacy) moderates the association between the degree of AI usage and decision quality.

While there might be a link between using AI technologies and enhanced performance among organizations, it is an indirect link and largely dependent on improved decision making. In other words, when employees can effectively use AI technologies, they will make decisions that are more accurate, quick, and data-driven, which would result in an improvement in their performance [2,15]. From this, one can deduce that decision-making quality is the mediating variable between using AI and achieving improved performance.

It is, however, important to emphasize that the strength of the indirect connection will vary depending on people's interaction with AI technology. Relying on the theoretical framework of trust in automation, high trust in AI technology can make people depend highly on AI decisions, which can undermine the effect of using AI for decision-making [8]. In a similar vein, an employee's level of AI literacy affects his or her ability to properly analyze AI-driven insights, which in turn affects how much use of AI translates to better decisions and hence improved performance [10]. It appears, therefore, that this indirect relationship between AI use and improved performance, via decision-making, may not always hold because it depends on the level of AI trust or AI literacy.

H5

The indirect impact of AI use intensity on organizational performance via decision quality is contingent upon AI trust (or AI literacy).

Research Design

For this study, a quantitative and cross-sectional design was utilised to analyse the impact of the intensity of the use of AI technology on the quality of decisions, AI trust (AI literacy), and organizational performance. The use of such research design was deemed to be appropriate because it would allow for empirical testing of the hypothesized relationship between independent and dependent variables. Furthermore, it is possible to collect standardised information in a cross-sectional study and conduct an analysis involving multiple variables. Behavioural science and management research rely heavily on the cross-sectional design when investigating relationships between variables.

The data for this research was obtained from people who worked in the IT and ITES industries in Bengaluru and who actually utilize the AI tool in the process of work. The research involved the use of a purposeful sampling design where the participants were selected depending on whether they had experience using AI technology. The data was collected through structured instruments (questionnaires). Initially, 350 responses had been received, but out of those 44 had been omitted because of lack of consistency and completeness of responses. Hence, 306 questionnaires were finally selected, which made up approximately 87.4 percent of total respondents, considered satisfactory for the research purposes.

All the latent variables were measured using reliable measures obtained from past research works, and all were measured using a five-point Likert scale with 1 denoting strongly disagree and 5 representing strongly agree. The degree of adoption of AI was measured using measures developed based on scales used to measure the extent of adoption of technology and its capabilities [2,5]. Decision quality was measured using scales measuring the accuracy, speed, and data use in decision-making processes [15,17]. Trust in AI (AI literacy) was measured using scales measuring either trust in AI systems or understanding of AI outputs [8,10]. Organizational performance was measured using subjective performance measures as recommended by past research [5,18].

Testing of the stated hypotheses was done using Hayes PROCESS Model 7 where 5000 bootstrapping samples were used. Such a process allowed for the analysis of both mediation and moderation together with conditional indirect effects. The assessment of reliability and validity was conducted using established means. All constructs had Cronbach's alpha coefficients that were higher than the minimum 0.70 level. In other words, the measures used showed satisfactory internal consistency. Moreover, composite reliability coefficients were also higher than minimum acceptable. The average variance extracted (AVE) criterion was fulfilled as well. It proved convergent validity. Discriminant validity was achieved as well (Figure 1).

To enhance the quality of regression analysis, the assumptions of regression were tested before conducting any hypothesis test on the data. The existence of common method bias was checked through Harman's one-factor test, which revealed that a single factor explained 27.84% variance, well below the acceptable level of 50%. Therefore, common method bias cannot be considered a major threat to the research findings. The problem of multicollinearity was tested by estimating Variance Inflation Factor (VIF), which turned out to be insignificant. Thus, multicollinearity is not present in the sample used in this research. Normality assumption was checked with the help of skewness and kurtosis tests, the results of which lie within the acceptable range. Linearity among the variables has also been ensured. Moreover, homoscedasticity has been confirmed as residual variances remain unchanged at different levels of the predictor variables. Independence of errors has also been proven. Hence, all the assumptions of regression have been satisfied.

Data Analysis

As far as demographics are concerned, there seems to be a balanced representation of various demographics among the respondents. Male respondents outnumbered the females, with around 55% of them being male and the rest being female respondents. In terms of age, the sample is young, where the majority falls under the age range of 30-35, followed by those falling under 30 and above 40 years respectively. With regard to educational qualification, postgraduates dominated the other two demographics of graduates and others. In relation to experience, most respondents had medium levels of experience of between 5 to 10 years. On the other hand, some respondents had low experience levels, below 5 years, while others had high experience levels, exceeding 10 years. The sample consisted of a variety of employment positions, with increased participation from the technical team, management level employees, analysts, and executives. In terms of exposure to AI, many of the respondents had experience levels in the range of one to five years when using AI tools, while only a few respondents had experience levels greater than five years. All respondents used AI tools every day (Table 2).

Table 2: Table Showing Demographic Profile of the Respondents

Factor	Category	Frequency	Percent
Gender	Male	167	54.58
	Female	139	45.42
Age	<30	109	35.62
	30-35	121	39.54
	35-40	51	16.67
	>40	25	8.17
Academic Details	Graduation	129	42.16
	Post-Graduation	145	47.39
	Others	32	10.46
Work Experience	<5 Year	84	27.45
	5-10 Years	156	50.98
	>10 Years	66	21.57
Job Role	Executive	41	13.40
	Manager	76	24.84
	Analyst	65	21.24
	Tech Team	93	30.39
	Senior Manager	31	10.13
Experience with AI tools usage	< 1 year	40	13.07
	1-3 Year	143	46.73
	3-5 Year	119	38.89
	> 5 Years	4	1.31
Frequency of usage of AI tools	Daily	306	100
	Weekly	-	-
	Occasionally	-	-

Table 3: Table Showing CFA Results

Items	C Alpha	Loadings	AVE	CR		SqrtAVE
AIUI1	0.841	0.783	0.627	16.411	0.783***	0.792
AIUI2		0.803			0.803***	
AIUI3		0.891			0.891***	
AIUI4		0.806			0.806***	
AIUI5		0.768			0.768***	
AIT1	0.799	0.846	0.623	16.492	0.846***	0.789
AIT2		0.875			0.875***	
AIT3		0.827			0.827***	
AIT4		0.712			0.712***	
AIT5		0.801			0.801***	
DQ1	0.863	0.767	0.573	14.070	0.767***	0.757
DQ2		0.768			0.768***	
DQ3		0.775			0.775***	
DQ4		0.705			0.705***	
DQ5		0.736			0.736***	
OP1	0.901	0.793	0.618	15.257	0.793***	0.786
OP2		0.775			0.775***	
OP3		0.821			0.821***	
OP4		0.713			0.713***	
OP5		0.804			0.804***	

AIUI=AI usage intensity, AIT = AI Trust, DQ = Decision Quality, OP = Organisational or Firm Performance. CMIN = 273.341, DF = 164, P<0.001, CMIN/DF = 1.667, SRMR = 0.056, RMSEA = 0.047(PCLOSE = 0.70), GFI = 0.913, AGFI = 0.911, NFI = 0.927, RFI = 0.937, IFI = 0.947, TLI = 0.938, CFI = 0.946s

Table 4: Heterotrait and Monotrait Ratio Matrix to Assess Discriminant Validity of the Measurement Model

Parameters	AIUI	AIT	DQ	OP
AIUI	1	-	-	-
AIT	0.645	1	-	-
DQ	0.613	0.605	1	-
OP	0.555	0.543	0.652	1

Table 5: Model Summary

Parameters		DV = DQ		DV = OP		
Constant	β	SE	LLCI (ULCI)	β	SE	LLCI (ULCI)
	-10.2764	2.1692	-14.545, -6.0077	1.1436	0.5176	0.1251, 2.1621
X	1.2076	0.104	1.0029, 1.4123	0.1820	0.0589	0.0660, 0.2979
M	-	-	-	0.7645	0.063	0.6406, 0.8884
W	0.9887	0.1337	0.7256,1.2518	-	-	-
X*W	-0.033	0.006	-0.0449, -0.0212	-	-	-
	R2	0.8718	-	R2	0.7989	-
	F (3, 302)	684.86	-	F (2, 303)	602.008	-

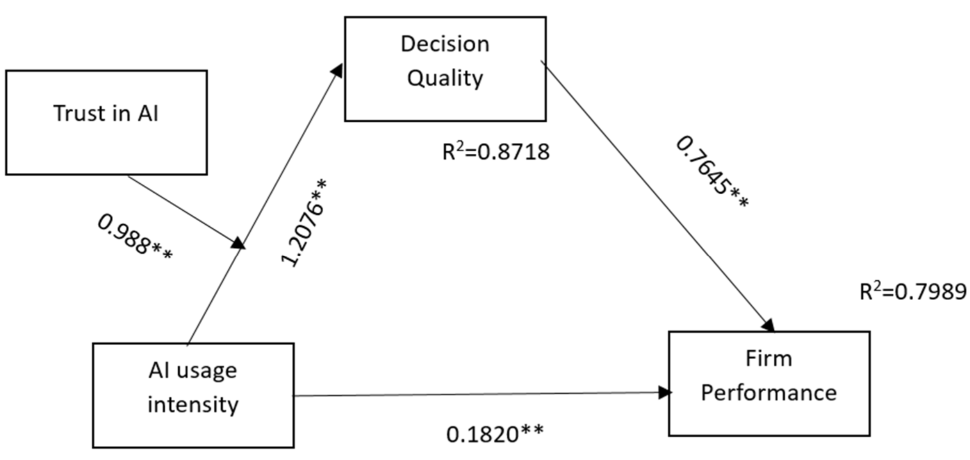

Figure 1: Proposed Research Model

To determine the fit of the measurement model, several fit indices were considered. As per the fit measures, there is a good model fit because of the following reasons: $\chi^2/df = 1.67$, and since this is less than the threshold of 3, the fit is good. Additionally, the SRMR value, which is 0.056 and lower than 0.08, indicates a good fit. In the same way, there is a close fit since the RMSEA value of 0.047, together with PCLOSE value of 0.70, indicate a good fit. Moreover, the incremental fit indices also show that the model has a good fit. Furthermore, GFI = 0.913, AGFI = 0.911, these values of absolute fit indices were well above the suggested cut-off value of 0.90 [16]. The model was also adjudged by considering incremental fit indices namely IFI = 0.939, CFI = 0.952, RFI = 0.941, TLI = 0.940, and NFI = 0.931 all these values were higher than the acceptable level of 0.90, indicating an adequate fit to the data [19-21].

Reliability and validity of the measurement model were measured on the basis of set criteria. According to Table 3, all constructs exhibited good levels of reliability, indicated by Cronbach’s alpha values varying between 0.799 to 0.901, above the threshold value of 0.70 [20]. Factor loadings for all the variables were also significant and above 0.70, signifying good reliability. Convergent validity was further proven since all constructs had AVE values lying between 0.573 and 0.627, which was greater than the minimum required value of 0.50 [22]. Moreover, all the CR values were above 0.70, which is the recommended value for the reliability of a construct [20].

The Heterotrait-Monotrait ratio (HTMT) was used to test the discriminant validity. According to Table X, the HTMT values were lower than the suggested cut-off value of 0.90 [20]. In particular, the HTMT values varied from 0.543 to 0.652, and the maximum HTMT value was recorded between organizational performance and decision quality (0.652). The second maximum HTMT value was found between AI usage intensity and Trust in AI (0.642), while the third was found between AI usage intensity and decision quality (0.613). All other HTMT values were relatively low and showed some association between variables, but no overlap (as all the values are <0.85), indicating a robust discriminant validity of the measurement model. Therefore, the measurement model shows sufficient reliability and validity of all constructs involved (Table 4).

A regression analysis was conducted to establish the relationship between the use intensity of artificial intelligence and AI trust on decision quality. The proposed model was statistically significant, F (3, 302) = 684.8634, p = 0.0000 (<0.001). In addition, the proposed model was able to explain a major proportion of variance in the proposed mediating variable (decision quality) R2 = .8718, signifying that the proposed model was able to capture 87.18 percent variation in decision quality, demonstrating that the proposed model fits the data well (Table 5).

The findings obtained from the model show that the focal predictor AI usage intensity has a favourable robust influence on decision quality (β = 1.2076, SE = 0.1040, t = 11.6081, p<0.001, 95% CI (1.0029, 1.4123), implying the elevated use of AI tools in the organisation assists employees make more reliable, on-time, and evidence-based decisions. In the same way, the second variable Trust in AI has a favourable and statistically significant influence on decision quality (β = 0.9887, SE = 0.1337, t = 7.3946, p<0.001, 95% CI (0.7256, 1.2518), implying that employees who trust AI tools in the organisation likely to gain more benefit in terms of outcomes of quality decisions. On the other hand, the interaction effect of the proposed model (X ×W) was found to be negative (β = -0.0330, SE = 0.0060, t = -5.4830, p<0.001, 95% CI (-0.0449, -0.0212), shares inverse relationship, indicating that as AI trust amplifies, the direct and positive influence of AI usage intensity on decision quality becomes less pronounced. In simpler terms, even though AI usage very beneficial, leveraging heavily on it without careful consideration may diminish its overall efficiency in enhancing decision quality in the organization.

In addition, the interaction term (X ×W) of the proposed model was found to be significant R2 Change (ΔR2 = 0.0128, F(1, 302) = 30.0637 p = 0.0000 (<0.001), signifying that trust in AI tools in a substantive manner moderates the relationship between focal predictor of the model (AI usage intensity in the firm) and decision quality. Even though, the variance explained by the model is limited, it is statistically significant and contributes predictive power to the proposed model. To analyse the interaction between the variables in question, conditional effects were investigated. Specifically, the findings indicated that the effect of the intensity of AI usage on the decision quality is highest in individuals who have low levels of trust in AI (13.4360) (β = 0.7640, SE = 0.0330, t = 23.1517, p < .001, 95% CI (0.6991, 0.8289); the effect is lower in individuals with moderate levels of AI trust (17.8529) (β = 0.6182, SE = 0.0274, t = 22.5952, p<0.001, 95% CI (0.5643, 0.6720), and the weakest effect takes place in cases when there is high trust in AI (22.2699) (β = 0.472, SE = 0.0427, t = 11.0630, p < .001, 95% CI (0.3883, 0.5563). These findings imply that regardless of how high trust in AI can be, the usage of AI contributes to the decision quality. Nonetheless, as mentioned above, when the level of AI trust is moderate, people tend to use AI more effectively (Table 6).

Table 6: Conditional Effect of Focal Predictor at Various Levels of Moderator

AIT	Effect	se	t	p	LLCI	ULCI
13.436	0.764	0.033	23.1517	0.0000	0.6991	0.8289
17.8529	0.6182	0.0274	22.5952	0.0000	0.5643	0.672
22.2699	0.4723	0.0427	11.063	0.0000	0.3883	0.5563

*X*W: R^2 Change*

Rable 7: Indirect Effect of Focal Predictor (Aiui) on Outcome Variable (Firm Performance) Via Dq

AIT	Effect	BootSE	BootLLCI	BootULCI
13.436	0.5841	0.1056	0.4099	0.8236
17.8529	0.4726	0.0849	0.335	0.6657
22.2699	0.3611	0.084	0.2251	0.5457

Table No 8: Table Showing Index of Moderated Mediation

Parameters	Index	BootSE	BootLLCI	BootULCI
AIT	-0.0252	0.0099	-0.0468	-0.0083

Table 9: Pairwise Contrasts Between Conditional Indirect Effects (Effect 1 – Effect 2)

Contrast	BootSE	BootLLCI	BootULCI
-0.1115	0.0435	-0.2066	-0.0365
-0.223	0.0871	-0.4132	-0.0729
-0.1115	0.0435	-0.2066	-0.0365

A regression analysis was used to test the influence of both AI usage intensity (focal predictor) and decision quality (proposed mediating variable) on organisational performance. The general regression model turned out to be statistically significant, F (2, 303) = 602.0077, p<0.001, explaining almost 80% variance in the organisation performance (R^2 = 0.7989). According to the results obtained through regression, there exists a positive and statistically significant relationship between the use intensity of AI solutions and organisational performance (β = 0.1820, SE = 0.0589, t = 3.0878, p = 0.0022, 95% CI (0.0660, 0.2979). This indicates that the increasing use of such technologies can be associated with an increase in firm performance. Another latent variable, namely decision quality, has a highly positive influence on performance (β = 0.7645, SE = 0.0630, t = 12.1435, p = 0.0000 (<0.001), 95% CI (0.6406, 0.8884). In other words, a greater emphasis should be placed on making high-quality decisions in order to enhance organisational outcomes. It should be mentioned that the impact of decision quality exceeds that of AI usage substantially. It has been revealed that there exists a statistically significant interaction effect between AI usage intensity and decision quality (F (1, 302) = 65.78, p<0.001). This means that the influence of AI use intensity varies according to decision quality levels.

It can be seen from the results that the impact of intensity of using AI on the performance of organisations is significantly positive (β = 0.1820, SE = 0.0589, t = 3.0878, p = 0.0020, 95% CI (0.0660, 0.2979). Hence, there is evidence that AI helps improve organisational performance regardless of the quality of decision-making. In order to evaluate the mediation process, conditional indirect effects have been estimated for various values of AI trust. It is worth noting that the indirect effect of the influence of AI usage on performance through decision quality is always significant since confidence intervals do not include zero. The indirect effect at low levels of trust in AI (13.4360) (β = 0.5841, BootSE = 0.1056, BootCI (0.4099, 0.8236); the indirect effect is lower with moderate levels of AI trust (17.8529) (β = 0.4726, BootSE = 0.0849, BootCI 0.3350, 0.6657), and the weakest effect takes place in cases when there is high trust in AI (22.2699) (β = 0.3611, BootSE = 0.0840, BootCI (0.2251, 0.5457). Nevertheless, with an increase in AI trust, the indirect effect gradually decreases. Thus, it is the most significant for low values of AI trust (effect = 0.584), less significant for medium-levels of AI trust (effect = 0.473) and the least significant for high AI trust (effect = 0.361). From these results, it follows that the use of AI can significantly help improve performance through better decisions, but this effect becomes less noticeable with an increase in the level of AI trust (Table 7).

The result for the index of moderated mediation was shown to be significant and negative (Index = -0.0252, BootSE = 0.0099, 95% CI (-0.0468, -0.0083) since the confidence interval does not contain zero. It shows that the indirect effect of AI use intensity on organisational performance via decision quality significantly differs depending on the level of AI trust, which means moderated mediation is supported. Moreover, the results of comparing the conditional indirect effects also point out a clearly decreasing pattern. The indirect effect in the case of medium levels of AI trust is significantly smaller compared to low levels of AI trust (difference = -0.1115, BootSE = 0.0435, 95% BootCI (-0.2066, -0.0365), whereas high levels of AI trust yield an even lower indirect effect compared to low levels (difference = -0.2230, BootSE = 0.0871, 95% BootCI (-0.4132, -0.0729). Also, the indirect effect at the medium levels is significantly lower than at high levels of AI trust (difference = -0.1115, BootSE = 0.0435, 95% BootCI (-0.2066, -0.0365). Thus, the analysis showed that an increase in AI trust leads to a decrease in the effect of AI use intensity on performance via decision quality (Table 8,9).

Inference: The results of the current study offer robust support for a moderated mediation model involving the relationship among the intensity of AI usage, decision quality, AI trust, and organizational performance. In accordance with previous research, it has been determined that the intensity of AI usage has a positive impact both on decision quality and organizational performance. The results thus provide further evidence that AI helps enhance the analytical skills of individuals and improve the performance of related tasks [2,5]. Decision quality turned out to be a crucial

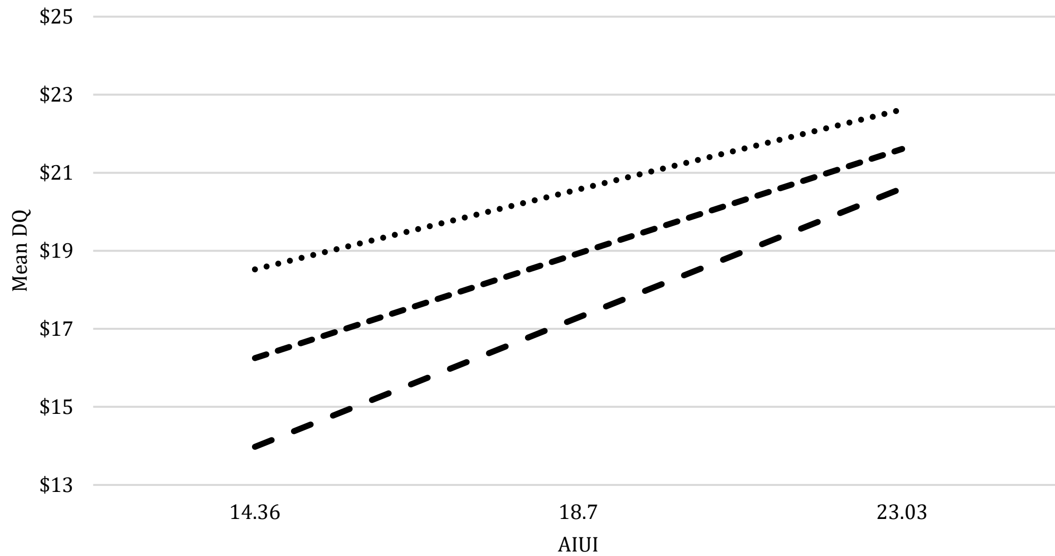

Figure 2: Graph Showing the Moderation Effect of and Trust in AI On Focal Predictor (AI Usage Intensity) and Decision Quality

mediator, driving performance in an organization, which is in line with the previous findings on the importance of data-driven decision-making [15,17]. However, unlike previous literature, the current study found that AI trust serves as a complex moderator, having an unexpected role in the relationships under consideration. Contradicting the previous findings on the positive impact of trust on effective AI use [8], the study found that higher levels of AI trust have a negative moderating effect on the positive relationship between AI usage and decision quality and, consequently, on organizational performance indirectly. In general, this study provides new insights into the field of human-AI interaction, demonstrating that AI will work best when combined with critical human thinking. Instead of implementing more technologies into organizational processes, companies need to teach their employees how to use them properly. Therefore, this paper makes a contribution to the existing literature since it simultaneously considers both the mechanism and the boundary conditions of the phenomenon under investigation (Figure 2).

The interaction graph shows that AI use has a positive correlation with decision quality regardless of the degree of trust in AI; however, there is a systematic difference in the strength of the relationship based on the level of AI trust. For instance, the slope of the relationship is highest for low degrees of trust and gets smaller for medium and high degrees of trust. These results indicate that although AI use improves decision quality, the improvement effect is minimal at high degrees of trust in AI (Figure 2).

DISCUSSION AND CONCLUSION

The results of this study offer valuable insights on how the use of AI leads to organizational performance via decision-making activities. In line with previous research, the use of AI at high intensities increases the quality of decisions made, leading to better organizational performance. This is aligned with the growing literature on the benefits of AI in terms of better decision-making [2,15]. In addition, since decision quality plays an essential role in organizational success, it can be said that organizations will find greater value in their AI adoption efforts through making smart, timely, and evidence-based decisions using AI [5,17].

In this regard, decision quality emerges as an important mediating variable that connects technological inputs to performance outputs. Notably, a major contribution of this study is the identification of the complex role played by AI trust in the use and effectiveness of AI. Contrary to previous studies, which suggest that trust serves as a facilitator of AI usage [8], the findings of this study indicate that high AI trust negatively moderates the effect of AI use on decision quality. It implies that too much trust may result in dependency on AI outputs at the expense of critical thinking. These results resonate with recent studies on automation bias in the form of excessive acceptance of algorithmic suggestions without appropriate consideration [9]. As such, one can argue that the results contradict the common belief that high levels of trust are better in all cases. Moreover, the analysis of moderated mediation reveals that the influence of AI use on organizational performance via decision quality becomes smaller when the level of AI trust rises. Thus, the efficiency of artificial intelligence cannot be attributed to its use alone; it is also necessary to take into account the perception and application of AI. The results expand the existing literature by considering both aspects of human-AI interaction (the process and the context) simultaneously [3,7].

In summary, it has been established in this paper that the adoption of AI technology does not necessarily translate into improved performance at an organizational level. On the contrary, its benefits accrue from the superior quality of decisions that it facilitates, serving as an important mediator in the relationship between AI and performance. Meanwhile, the importance of AI trust has been overstated in previous studies, as it can undermine the advantages of AI technology by decreasing its rigorous assessment. In other words, the results of the analysis point to the fact that the application of AI technologies should be considered as part of a larger human-AI system, rather than a purely technical process.

Managerial Implications

Several managerial implications arise from the results of the research. Firstly, it is important that organizations not only concentrate on the growth in AI implementation but also enhance their decision-making processes. Training should be implemented for staff in order to assist them in interpreting the output of AI algorithms. Secondly, managers must refrain from fostering an environment of uncritical acceptance of the results generated by AI algorithms. Although trust is required, too much can lead to detrimental effects. Finally, companies must consider the development of competencies that can support their ability to work with AI. For example, employees can be trained on their ability to think analytically and gain a general understanding of AI to make sure they can work in conjunction with these technologies [10]. In this way, a balance can be achieved whereby the company uses AI to enhance human decision-making rather than replacing it completely. The last recommendation involves the use of AI systems that foster transparency and explainability as a means of informing users.

Limitations of the Study and Suggestions for Further Research

Though the research conducted by the author is very rich in insights, there are also some limitations to the research that must be taken into account. The first limitation is associated with the fact that the current study uses a cross-sectional approach, so it becomes impossible to draw any causal relationship between the variables under investigation. However, future research could examine the same issue with regard to the other approach (longitudinal or experimental). The second limitation involves data gathering in just one industry and one particular geographic region. Thirdly, as this is a study based on self-reports of participants, there is an issue related to the potential presence of a response bias despite the attempt to eliminate statistical biases associated with the methodology used. Further research may consider multi-methods data collection to ensure the robustness of conclusions obtained. Furthermore, while this study considered AI trust (also known as AI literacy) as a moderating variable, there could be other moderating variables (e.g., complexity of tasks, organizational culture, or AI transparency). The analysis of these variables would allow for a better comprehension of the interaction between humans and AI systems. Lastly, the study reveals a negative moderating effect of AI trust, implying that too much trust towards AI tools can have a detrimental effect on decision-making performance. Future studies can analyse the issue further through the investigation of nonlinear effects or finding out optimal trust level towards AI applications.

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