

The Impact of Responsible Artificial Intelligence Governance on Firms' Competitive Performance: An Analytical Study of the Mediating Role of Knowledge Management Capabilities

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Abstract:

This study aims to examine the impact of responsible AI governance on the competitive performance of Algerian economic institutions, with knowledge management as a mediating variable. Therefore, a questionnaire was distributed to 63 department officials and decision makers in public and private economic institutions. The results showed that responsible AI governance has no direct impact on competitive performance, but it does have a positive impact on knowledge management. The results also demonstrated a positive effect of knowledge management capabilities on organizations' competitive performance and served as a partial mediator in the relationship between responsible AI governance and competitive performance.

Keywords: Responsible AI governance; Knowledge Management Capabilities; Competitive Performance; Direct effect; Indirect effect.

Jel Classification Codes: O32, L25, O33, D83

1. INTRODUCTION

The world has recently witnessed major transformations as a result of the digital revolution and the widespread spread of artificial intelligence applications, which have become an integral part of economic, social, and administrative life. These applications have become important tools for improving decision quality, increasing efficiency, and enhancing organizations' competitiveness. This development was not limited to developed countries only, but has become a reality in all countries, including Algeria. However, this rapid development raises ethical and regulatory challenges related to protecting privacy, ensuring transparency, and avoiding bias. From it emerged the concept of responsible AI governance as a framework for regulating the use of these applications and ensuring their safe and ethical employment. In addition, the effectiveness of AI use in organizations depends on their ability to manage knowledge, which is the primary resource for these applications. Therefore, this study aims to examine the relationship between artificial intelligence governance and its impact on the competitive performance of Algerian economic institutions, with a focus on the role of knowledge management capabilities

2. Theoretical framework

Artificial intelligence has received increasing attention from institutions and society, as economic institutions have moved in recent years towards relying on artificial intelligence to digitize their activities, as it contributes to digital transformation by providing solutions based on available data. Artificial intelligence technologies also offer new opportunities that can be exploited, enhancing the motivation of institutions and the global economic system to transform through artificial intelligence (Rodrigues, Ferreira, Teixeira, & Zopounidis, 2022).

In addition, the ability of artificial intelligence to perform precise tasks efficiently and in a short time has led to an increase in individuals' dependence on this technology (Shabbir & Anwer, 2015). Möhring and Keller define artificial intelligence as "an attempt to simulate cognitive and human capabilities via a computer." (Papagiannidis , Enholm , Dremel, & Mikalef , 2023), While Kaplan and Haenlein define it as "the ability of a system to accurately interpret external data, learn from it, and use this knowledge to achieve specific goals through flexible adaptation." (Kaplan , Haenlein, & Siri, 2019). By this definition, artificial intelligence can be considered a system capable of generating results on its own and taking actions to achieve specific goals, which are directly or indirectly related to the directions of institutions. According to Mikalef and Gupta, "AI should not be likened to human capabilities, because many AI applications used in organizational environments exhibit characteristics that complement human capabilities, meaning that they do not seek to imitate humans, but rather enhance and support their efficiency and performance within the organization." (Mikalef & Gupta, 2021)

Artificial intelligence tools give a competitive advantage to their users, thanks to their ability to process large amounts of data, making them an influential tool in decision-making, predicting trends, and enhancing information control within organizations (Shabbir & Anwer, 2015)

However, the potential of AI has not yet been fully exploited, prompting some major companies like Google to adopt responsible AI governance to improve performance and reduce potential negative impacts (Google, 2025), IBM has also developed a set of tools to address issues of fairness and justice in the use of artificial intelligence (de Laat, 2021). Responsible AI is defined as "the process of designing, developing, and implementing AI

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systems in a way that empowers individuals and organizations, while ensuring equitable impact on customers and society, helping organizations build trust in AI technologies." (Papagiannidis, Mikalef, Krogstie, & Pappas). In order to achieve a competitive advantage over competitors, many organizations have implemented and applied artificial intelligence solutions with the aim of automating their processes, increasing efficiency, and reducing costs. To achieve these goals, AI governance is essential (Papagiannidis, Enholt, Dremel, & Mikalef, 2023). Butcher and Beridze define AI governance as: "a diverse set of tools, solutions, and mechanisms that influence the development of AI and its applications." (Butcher & Beridze, 2019).

The principles of responsible artificial intelligence can also be summarized in the following points: (Papagiannidis, Mikalef, & Conboy, Responsible artificial intelligence governance: A review and research framework, 2025)

1-Accountability: Its presence is considered a necessity in the organization as it allows responsibilities to be clearly defined and enables decisions to be audited at every stage of system development and operation. accountability depends on two basic elements:

- **Auditability:** This refers to the ability to examine algorithms, data, and system design.
- **Responsibility:** It is concerned with identifying the entity responsible for supervision and follow-up within the institution.

However, implementing accountability is difficult due to the complex nature of AI systems, so tools must be developed to help detect errors and enhance transparency, especially since organizations may be subject to criticism in the absence of clear accountability. (de Almeida, dos Santos, & Farias, 2021)

2- Diversity, non-discrimination, and fairness: These are considered the basics of responsible artificial intelligence and include:

- **Accessibility:** design of systems in a manner that makes them accessible and usable for everyone, regardless of age, gender, abilities, or characteristics.
- **No unfair bias:** inclination of prejudice toward or against people, objects, or positions, as well as inherent biases in datasets, which can precipitate undesirable outcomes. Therefore, it is necessary to ensure that data is distributed in a balanced manner, is constantly reviewed and updated, and that information is processed and analyzed in accordance with basic ethical values to reduce any form of bias as much as possible. (Fjeld, Achten, Hilligoss, & Nagy, 2020)

3- Human agency and oversight: The role of the individual is represented in the user's ability to understand and interpret the results, in addition to ensuring the application of artificial intelligence systems to societal values, justice and democracy, including:

- **Human review:** This refers to the presence of the human element in the decision-making process and monitoring of systems. It also gives individuals the right to review and object to decisions taken by the system.
- **Human well-being:** It is considered an essential factor in developing artificial intelligence systems because it ensures that these technologies contribute to improving the quality of life of individuals and promoting their interests. (Singapore Government, 2020)

4- Privacy and Data Governance in AI: Data privacy and governance refer to the principles of how to manage data securely and effectively when developing AI systems, taking into account their availability, quality, and security. Includes:

- **Data quality:** that is, the accuracy of the information and its suitability to reality.
- **Data privacy:** It means protecting and controlling information throughout its life cycle.
- **Data access:** Control of data in accordance with national and international rights laws.

To ensure these principles, the data life cycle must be documented, data collection methods and sensitivity continuously evaluated, and compliance with various legal regulations must be ensured, taking into account cultural and environmental differences between countries, as these affect the quality of data, data collection methods, and data use.(Matthews, 2020)

5- Technical robustness and safety: This refers to designing artificial intelligence systems in a way that allows them to deal with risks, ensures continued performance as planned, and minimizes unintended damage. These systems must be characterized by:

- **Accuracy:**To operate reliably, while minimizing errors and unintended damage.
- **Reliability:**To enable it to make the right decisions and adapt to different inputs and conditions.

- **General safety:**having emergency plans to ensure continued operation in cases of problems or attacks.

- Flexible:**to protect them from vulnerabilities and hacks that attackers may exploit, to ensure that results are always reliable and secure.(Singapore Government, 2020)

6- Transparency: aims to enhance users' understanding of how systems work and increase trust in them. It includes several main aspects such as:

- **Explainability:** The ability to clarify the technical processes of the system and the decisions resulting from them.

- Communication:** It is the individual's right to obtain prior information when dealing with an artificial intelligence system.

- **Traceability:**The ability to track data and processes that led to system decisions, including data collection, labeling, and algorithms used.

Transparency also helps detect errors and increase confidence in results, provided users are aware that they are dealing with an AI system and not a human.(Fjeld, Achten, Hilligoss, & Nagy, 2020)

7-Social and environmental well-being: It constitutes an important part of responsible artificial intelligence in terms of:

- Environmental well-being:** Artificial intelligence systems must be designed in an environmentally friendly manner that takes into account climate issues, while studying resource and energy consumption during development and operation

- Social well-being:** This includes assessing the impact of AI on society in several areas, such as work and education. AI systems can improve safety in hazardous occupations or lead to changes in the labor market and social organization methods, but they may reduce direct social interaction.

The risks of misuse of artificial intelligence in democratic processes and political decision-making must also be taken into account, which requires a careful study of the impact of these systems on society and planning for their responsible use. (Singapore Government, 2020)

In addition to ethical aspects, developing responsible AI applications gives organizations a sustainable competitive advantage. Knowledge Management Capabilities (KMC) enable organizations to search for and exchange up-to-date knowledge to meet needs, exploit innovation opportunities, and respond to changes in the market, leading to high and continuous organizational performance (Papagiannidis , Enholm , Dremel, & Mikalef , 2023). Knowledge management is the foundation for transforming data and information generated by artificial intelligence into organizational knowledge that enhances competitiveness. Therefore, integrating responsible AI governance with knowledge management capabilities is vital to foster innovation and excellence in dynamic markets.

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Therefore, the integration between responsible AI governance and knowledge management capabilities is a pivotal factor in enhancing organizations' ability to innovate and excel in dynamic markets.

Based on the above, we will try to study this topic based on the following problem:

How does responsible AI governance impact the competitive performance of Algerian economic institutions, and what role do knowledge management capabilities play in explaining this relationship?

To answer the previous problem, we propose the following conceptual model:

Fig.1. Conceptual model of the study



Source: Prepared by the researchers

Through the previous conceptual model, we propose the following hypotheses:

Hypothesis 01: Responsible AI governance positively impacts knowledge management capabilities.

Hypothesis 02: The governance of responsible artificial intelligence positively affects the competitive performance of Algerian economic institutions.

Hypothesis 03: Knowledge management capabilities positively affect the competitive performance of Algerian economic institutions.

Hypothesis 04: Knowledge management capabilities play a mediator role in the relationship between responsible AI governance and the competitive performance of Algerian economic institutions.

3. METHODS AND MATERIALS:

To address the previous problem and verify the validity of the hypotheses, we sent a questionnaire to department Managers and decision-makers in Algerian economic institutions. The sample size reached 63 individuals distributed across 7 economic institutions in Algeria, 2 public and 5 private. We also relied on structural equation models (PLS-SEM) to analyze the results because they are suitable for this type of study, as they allow the analysis of direct and indirect relationships and intermediate effects, in addition to not relying on assumptions that the variables follow a normal distribution, as well as because the study of small samples distinguishes them. To build the questionnaire, we relied on scales developed by leading researchers in this field. To measure the governance of responsible artificial intelligence (AI), the scale developed by Emmanuel Papagiannidis et al. was used. It is a second-order formative model consisting of 7 dimensions. (Papagiannidis, Mikalef, & Conboy, Responsible artificial intelligence governance: A review and research framework, 2025). To measure knowledge management capabilities (KMC) and competitive performance (CA), we

relied on the scale developed by Hongyi Mao et al., which are first-order reflective variables (Mao, Liu, Zhang, & Deng, 2016)

4. RESULTS AND DISCUSSION :

To be able to test the study hypotheses and validate the conceptual model that we built, we relied in estimating features on the (PLS-SEM) method because of the special advantages it offers related to natural distribution and sample size, in addition to its ability to study complex models. As we previously presented the measurement ladders that were relied upon to measure the study variables, which contain second-order latent variables of the type (formative-formative), we relied on the two-step method to estimate (Higher-Order Constructs –HOC-), as it provides more accurate results than the extended model method for recurring indicators. In this research, we will evaluate the first-order measurement model, which represents the first step of the two-step method (Two Stage Approach), then evaluate the measurement model for the second-order variables (Step Two), and finally evaluate the structural model.

4.1 First-order Formative measurement models

PLS-SEM is the preferred approach when formative constructs are included in the structural model. The measurement model of the study was assessed using SmartPLS4. To assess the formative measurement models, the variance inflation factor (VIF) is used to evaluate the collinearity of the formative indicators. The VIF values are lower than 3 for all indicators. In the second step, we assessed the indicator weights' statistical significance and relevance. PLS-SEM is a nonparametric method, and therefore, bootstrapping is used to determine statistical significance. If the confidence interval of an indicator weight includes zero, this indicates that the weight is not statistically significant and the indicator should be considered for removal from the measurement model. However, if an indicator weight is not significant, it is not necessarily interpreted as evidence of poor measurement model quality. Instead, the indicator's absolute contribution to the construct is considered, as defined by its outer loading (the bivariate correlation between the indicator and its construct). According to Hair et al, indicators with a nonsignificant weight should definitely be eliminated if the loading is also not significant. A low but significant loading of 0.50 and below suggests that one should consider deleting the indicator, unless there is strong support for its inclusion on the grounds of measurement theory (Hair, Risher, Sarstedt, & Ringle, 2019). Which is the case of (Acc1, data1, Div2), we notice that the indicator weights are not significant, but its outer loadings are above 0.50 and significant, so we kept the indicators as shown in Table 2.

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Table 1. Formative Indicator Assessment

HOC	LOC	item	outerweights	P - values	2.5%	97.5%	outerloading	P - values	VIF
responsible AI governance	Accountability	Acc1	0.345	0.088	-0,080	0,723	0.739	0.000	1,341
		Acc2	0.780	0.000	0,419	1,040	0.954	0.000	1,341
	Privacy and Data Governance	data1	0.233	0.156	-0,054	0,594	0.661	0.000	1,326
		data3	0.864	0.000	0,517	1,021	0.979	0.000	1,326
	Diversity, non-discrimination	Div1	0.717	0.001	0,243	1,043	0.953	0.000	1,604
		Div2	0.384	0.100	-0,077	0,832	0.824	0.000	1,604
	Technical robustness and safety	saf1	0.459	0.043	-0,025	0,864	0.846	0.000	1,527
		saf2	0.659	0.002	0,188	1,014	0.929	0.000	1,527
	Human agency	hum1	0.565	0.001	0,178	0,842	0.874	0.000	1,402
		hum2	0.576	0.000	0,257	0,888	0.879	0.000	1,402
	Transparency	trans2	0.423	0.010	0,091	0,735	0.716	0.000	1,176
		trans3	0.757	0.000	0,424	0,971	0.921	0.000	1,176
	environmental well-being	well_b1	0.419	0.093	-0,168	0,813	0.692	0.000	1,143
		well_b2	0.772	0.000	0,397	1,049	0.920	0.000	1,143

Source: From SmartPls output

4.2 Reflective measurement models

To assess the reflective measurement models, we focused on reliability, convergent validity, multicollinearity, and overall model fit. The results confirm that the measurement constructs meet the accepted psychometric standards and are suitable for structural model evaluation. To assess internal consistency reliability, Composite Reliability (CR) and Cronbach's Alpha were examined. All constructs exhibited CR values above the recommended threshold of 0.70, indicating satisfactory internal consistency. Similarly, Cronbach's Alpha values exceeded 0.70 for all constructs, suggesting strong reliability in the items used to measure each latent variable. Convergent validity was evaluated through the Average Variance Extracted (AVE). Each construct showed an AVE greater than 0.50, which indicates that more than half of the variance in the indicators is captured by the construct, meeting the standard criterion. Moreover, factor loadings for all items were above 0.60, further supporting the adequacy of each item in representing its respective construct. Multicollinearity was assessed using the Variance Inflation Factor (VIF), and all values were found to be below the threshold of 5, as shown in Table 2. (Hair , Hult , Ringle , & Sarstedt , 2017)

Table 2. Reflective Indicator Assessment

construct	item	loading	cronbach's α	CR (rho_a)	CR (rho_c)	AVE	VIF
competitive performance (CA)	CA1	0,872	0,845	0,864	0,906	0,762	1,885
	CA3	0,847					2,059
	CA4	0,899					2,227
Knowledge management capabilities (KMC)	KMC1	0,851	0,863	0,869	0,901	0,647	2,249
	KMC4	0,813					1,906
	KMC5	0,793					2,054
	KMC6	0,839					2,345
	KMC7	0,719					1,572

Source: From SmartPls output

4.3 Discriminant validity

Discriminant validity was assessed using two complementary methods: the Heterotrait-Monotrait Ratio (HTMT) and the Fornell-Larcker criterion. HTMT is a robust approach that evaluates the distinctiveness of latent constructs in structural equation modeling. As recommended by Henseler et al. (Henseler, Ringle, & Sarstedt, 2015), HTMT values should be below 0.90 to confirm discriminant validity. In this study, all HTMT values met this criterion, indicating that the constructs are empirically distinct (see Table 3).

Additionally, the Fornell-Larcker criterion was applied to cross- validate the discriminant validity findings. According to this method, the square root of the Average Variance Extracted (AVE) for each construct should exceed its correlations with other constructs (Fornell & Larcker) As presented in Table 4, all constructs satisfied this condition, further confirming the discriminant validity of the measurement model.

Table 3. Discriminant validity assessment using HTMT ratios.

	Heterotrait-monotrait ratio (HTMT)
KMC <-> CA	0,795

Source: From SmartPls output

Table 4. Discriminant validity assessment using the Fornell-Larcker criterion.

<u>Fornell-Larcker criterion</u>		
	CA	KMC
CA	0,873	
KMC	0,699	0,804

Source: From SmartPls output

4.4 Second-order Formative measurement models

After calculating the Scores factors of the formative variables and entering them as indicators of the second-order variable, we test the significance of the weights in the same previous way, as the results were as shown in Table 05, where we note that all values are significant, also for testing the collinearity of the second-order model by calculating the coefficient of variation inflation (VIF) when we note that all values are less than 3.

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Table 5. Second-order Formative Indicator Assessment

HOC	outerweights	P values	VIF
Acc	0.199	0.000	2.216
Data	0.195	0.000	2.696
Div	0.178	0.000	2.703
Hum	0.214	0.000	2.732
trans	0.188	0.000	1.917
well_b	0.143	0.000	2.081
saf	0.181	0.000	2.618

Source: From SmartPls output

4.5 Analysis of the structural model

4.5.1. Direct effects analysis

The study identified two significant direct relationships among the key variables. Specifically, responsible AI governance demonstrated a strong positive effect on Knowledge management capabilities ($\beta = 0.776$, $p < 0.000$), indicating that Governance principles such as transparency, accountability, and data organization contribute to improving the collection, storage, and exchange of knowledge within the organization. Likewise, Knowledge management capabilities significantly increased the competitive performance ($\beta = 0.524$, $p < 0.003$), whereas there is no significant direct relationship between responsible AI governance and the competitive performance ($\beta = 0.216$, $p < 0.216$). These findings provide empirical support for H2 and H3, while H1 was not supported as originally hypothesized. The direct effects are outlined in Table 6. Fig. 2 illustrates the results of the path analysis.

4.5.2. Mediation effects analysis

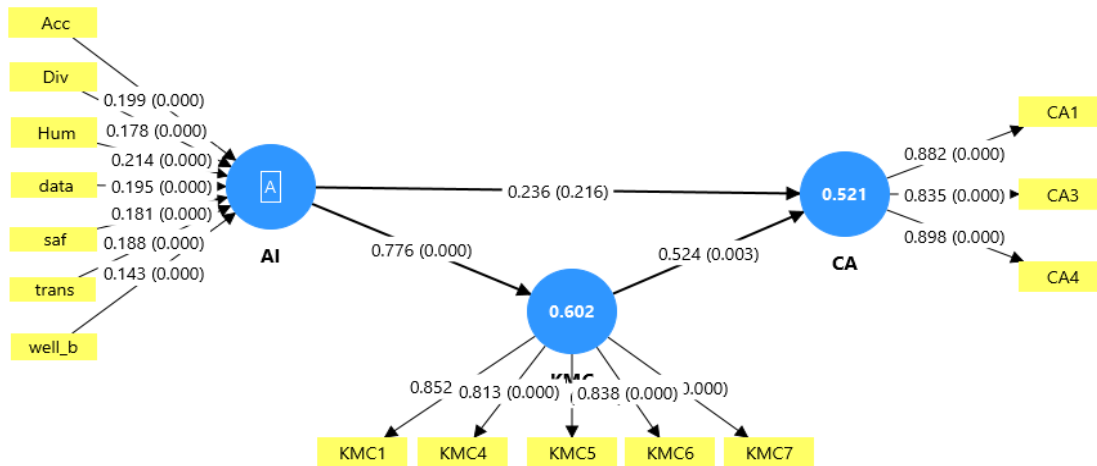
The results support partial mediation for the hypothesized relationship. Knowledge management capabilities partially mediate the effect of responsible AI governance on competitive performance ($\beta = 0.406$, $p < 0.005$).

Table 6. Results of the hypothesis

Hypothesis (Path)	β	T statistics	P values	Confidence intervals		Result
				2.5%	97.5%	
Direct effects :						
H ₁ : AI -> CA	0.236	1.236	0.216	-0.154	0.599	Not Supported
H ₂ : AI -> KMC	0.776	13.524	0.000	0.653	0.878	Supported
H ₃ : KMC -> CA	0.524	3.006	0.003	0.189	0.887	Supported
Mediating analysis :						
H ₄ : AI -> KMC -> CA	0.406	2.804	0.005	0.146	0.732	Supported

Source: From SmartPls output

Fig.2.Results of path analysis



Source:From SmartPls output

4.5.3. Interpretation of structural model evaluation results

Table 7 presents the coefficient of determination (R^2) and effect size (f^2) for the structural model. These values are essential to evaluate the model's explanatory (Hair , Hult , Ringle , & Sarstedt , 2017). The R^2 value for competitive performance (CA) is 0.521, indicating that Knowledge management capabilities (KMC) and responsible AI governance (AI) together explain approximately 52.1 % of the variance in (CA). Similarly, the R^2 Knowledge management capabilities (KMC) is 0.602, meaning that responsible AI governance explains 60.2 % of the variance in Knowledge management capabilities.

In terms of effect size (f^2), (AI) has an effect size of 0.515 on (KMC), and (KMC) has 0.228 on (CA), while (AI) has a moderate effect size of 0.145 on (CA). According to (Cohen, 1988), f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effect sizes, respectively. Therefore, all predictors in this model exert a small to moderate effect, reinforcing their meaningful contribution to the structural model.

Table 7.Structural model evaluation

Predictor	Outcome	R^2	R^2 Ajusted	f-square
AI	KMC	0,602	0,596	0,515
KMC	CA	0,521	0,505	0,228
AI	CA			0,04

Source:From SmartPls output

5. CONCLUSION

The results indicate no direct impact of implementing responsible AI governance on the competitiveness of Algerian institutions. This is due to the weak implementation of governance practices and the technological development of institutions, in addition to the lack of investment in this field. On the other hand, artificial intelligence governance has a positive impact on knowledge management capabilities, as governance principles such as transparency, accountability, and data organization contribute to improving the collection, storage, and exchange of knowledge within the organization. Investing in knowledge management also

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increases organizations' ability to innovate and make sound decisions, which leads to improving the quality of services and enhancing competitiveness. Knowledge management capabilities also play a partial mediating role in the relationship between responsible AI governance and organizational competitiveness. This means that governance indirectly impacts competitiveness through the development of knowledge management. However, this impact alone is not sufficient to fully explain the relationship, as there are other influencing factors that can be incorporated into the model, such as technological capabilities, the level of innovation, organizational culture, and the organization's digital readiness.

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8. APPENDICES:

1. responsible AI governancescales

Constructs	Sub-dimensions	Items	Measurment	Reference
responsible AI governance	Accountability	ACC1	-ability to assess AI applications concerning the algorithms, data, and design processes.	(Papagiannidis , Mikalef, & Conboy, Responsible artificial intelligence governance: A review and research framework, 2025)
		ACC2	-Oversight of the various stages and activities involved in AI deployment and how it should be allocated to people, roles, or departments.	
	Diversity, non-discrimination and fairness	Div1	-Design of systems in a manner that makes them accessible and usable for everyone, regardless of age, gender, abilities, and characteristics.	
		Div2	-Inclination of prejudice toward or against people, objects, or positions, as well as inherent biases in datasets, which can precipitate undesirable outcomes.	
	Human agency and oversight	Hum1	-Right of a person to challenge a decision made by an AI.	
		Hum2	-The notion that AI must include human well-being as a primary success factor for development.	
	Privacy and data governance	Data1	-accuracy of values in a dataset, matching the true characteristics of the entities described by the dataset.	
		Data2	-AI systems’ development and operation in a manner that considers data privacy throughout the data lifecycle.	
		Data3	-National and international rights laws during the design of an AI for data access permissions.	
	Technical robustness and safety	Saf1	-AI system’s ability to make correct judgments, such as correctly classifying information into the appropriate categories or	

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			being able to predict, recommend, or make intelligent decisions based on data or data models.	
		Saf2	-AI system's ability to work properly when subjected to a range of inputs or situational contexts.	
		Saf3	-safety rules and fallback plans that should be established for AI systems in the event of problems.	
		Saf4	-AI systems that should be protected against vulnerabilities that adversaries can exploit, e.g., hacking.	
	Transparency	Trans1	-Ability to explain the technical processes of an AI system and related human decisions (e.g., application areas of a system).	
		Trans2	-Human right to be informed in advance when interacting with an AI agent	
		Trans3	-Ability to track data and processes that yield the AI system's decision, including data gathering, labeling, and algorithms.	
	Social and environmental well-being	Well_b1	-Ubiquitous exposure to social AI systems in all areas of society, such as work and education.	
		Well_b2	-Most pressing environmental and climate concerns facing the planet.	

2. Knowledge management capability (KMC) and Competitive advantage (CA) scales

Constructs	Items	Measurment	Reference
Knowledge management capability (KMC)	KMC1	My organization has processes to gain knowledge on our suppliers, customers, and partners.	(Mao, Liu, Zhang, & Deng, 2016)
	KMC2	My organization can generate new knowledge from existing knowledge	
	KMC3	My organization has processes in place to distribute knowledge throughout the organization.	
	KMC4	My organization holds periodic meetings to inform employees about the latest innovations.	
	KMC5	My organization has formal processes to share the best practice among the different fields of activities.	
	KMC6	In my organization, knowledge is accessible to those who need it.	
	KMC7	My organization has processes for using knowledge to develop new products or services.	
Competitive advantage (CA)	CA1 CA2 CA3 CA4	Relative performance with respect to the competitors for the past three years Customer retention Sales growth Profitability Return on investment	Mao, Liu, Zhang, & Deng, 2016