7th Bangladesh Conference on Industrial Engineering and Operations Management
December 21-22, 2024
Publisher: IEOM Society International, USA DOI: 10.46254/BA07.20240219
Published: December 21, 2024

Navigating AI Adoption: The Role of Organizational Culture Under Disruption Severity

Nasif Morshed, Mushfiqur Rahman, and Kazi Md. Tanvir Anzum
Department of Industrial Engineering and Management
Khulna University of Engineering and Technology,
Khulna 9203, Bangladesh
morshed1911041@stud.kuet.ac.bd, rahman1911056@stud.kuet.ac.bd,
tanvir@iem.kuet.ac.bd

Abstract

This study proposes a novel framework to manage organizational agility in uncertain environments while exploring the interplay between organizational culture, disruption severity, and AI readiness and responsiveness to emerging types of disruption. The research draws its insights from the perspective of dynamic capabilities and asserts that organizational culture has the ability to guide AI integration at junctions when disruptions occur. It was based on a survey methodology of 383 respondents across 4 sectors – manufacturing, retail, IT services and healthcare. To validate hypothesized relationships, Partial Least Squares Structural Equation Modeling (PLS-SEM) was used. The results confirmed that organizational culture has a significant positive impact on AI readiness and responsiveness. Additionally, the results indicate that disruption severity is a key moderator, enhancing the effect of organizational culture in these particularly disrupted contexts. This shows two roles of organizational culture in ensuring technological capability as proactive and reactive. In this study, organizational culture and disruption management was unified within a framework to deliver unique insights into the strategic alignment of cultural and technological resources. To extend existing literature, and address gaps in the existing literature, the research considers the moderating role of disruption severity in dynamic environments. This is actionable guidance for organizations to better develop their technological adaptability, especially in a crisis. Future research on cultural dimensions as well as longitudinal impacts could enrich understanding as much as possible. The novel contributions of the study make it valuable to both academic and practitioner audiences interested in understanding organizational behavior and technology management.

Keywords
Organizational Culture, AI Readiness, AI Responsiveness, Disruption Severity, Dynamic Capabilities View

1. Introduction
AI technology is quickly infiltrating organizational structures, and this has highly influenced business processes, more so during periods of increased disruptions. Concerning recent events like COVID-19, it is evident that the AI capability is an imperative instrument for continuity of business and organizational success by addressing risks, planning, and recovery from shocks (Modgil, Gupta, et al. 2022). Consequently, these disruptions have demonstrated the potential of AI, as well as the fact that organizations are not yet ready to maximize the utilization of AI (Dey et al. 2024a). There are some difficulties an organization faces when it comes to attaining AI readiness and responsiveness. AI Readiness, the state of organization's readiness to effectively adopt AI technologies is mostly preceded by a foundation culture that embraces innovation and flexibility (Wong et al. 2024a). Similarly, operational responsiveness is the ability to effectively use AI in an organization's day to day workflow and addressing the operational requirements by embedded AI technologies into decision making. However, scenarios that disrupt the logistics substantially, for example, pandemics or disruptive supplies, make these challenges worse for several reasons, they deplete the existing resources and reveal the organizational voids (Chaudhuri et al. 2023).

Culture remains a very key component in the degree of organization readiness or responsiveness to Artificial Intelligence integration. Managers need a culture that facilitates collaboration, innovation and flexibility, so that if disruptions occur they can counteract with AI in central areas of operation (Wong et al. 2024a). On the other hand, severity of disruption moderates the correlation between organizational culture and support for AI driven strategies on the grounds that the intensity of interruption decides the degree to which culture in the organization can bolster AI driven strategic endeavors (Hussain & Papastathopoulos 2022). Although prior literature has examined facets of AI adoption and disruption, few studies focus on organizational culture, AI technologies, and the interaction of severity of disruption (Riad et al. 2024). Given previous premises, this study attempts to answer the following research question:

RQ1: What role does organizational culture play in determining how ready and responsive an organization is to unexpected disruptions through the impact of AI?

These gaps are addressed in this study by investigating the impact that organizational culture has on AI readiness and response, with emphasis on disruption severity as the moderating factor. Firstly, this research focuses on assessing the overall correlations between organizational culture and both the readiness for AI integration and the responsiveness to disruptions in the organization, and then aims to determine the moderating effect of the disruption levels on these correlations. The identified insights are envisaged to provide practical implications for organizations that wish to employ AI to support continuous operational performance and longevity.
Therefore, this study intends to answer a second research question, as follows:

RQ2: Can disruption severity play a moderating role in the effect of organizational culture on AI readiness and responsiveness? By addressing these questions, the intention of this study is to advance existing theory and theoretical frameworks which in the process can help to shed light as to how organizations can build their resistance and be better prepared for the level of uncertainty that is rapidly pervading existence.

1.1 Objectives

The specific objectives of this research are:

1. To investigate the direct influence of organizational culture on AI readiness and responsiveness.
2. To analyze the impact of disruption severity on AI readiness and responsiveness.
3. To assess the moderating role of disruption severity in the relationship between organizational culture and AI capabilities.

2. Literature Review and Theoretical Framework

Dynamic capabilities provide a key theoretical lens for studying how organizational culture mediates AI readiness and responsiveness to varying levels of disruption severity. Dynamic capabilities, defined as the firm's ability to reconfigure internal and external competencies to tackle changing environments in rapid time, serve as a key enabler for exploiting AI in disruptive situations (Ul Akram et al. 2024). Organizational culture is very much at the core of how AI readiness develops as it allows for adaptability, innovation, and resilience – elements that foster the path to AI adoption and integration (Bahrami & Shokouhyar, 2022). Similarly, the cultural values need to be aligned with technological agility and strategic objectives to achieve AI responsiveness — the ability to deploy and use AI in real-time (Bathaei, 2024). A moderating factor, disruption severity makes responsiveness an especially daunting challenge in crises of high intensity, for example the COVID-19 pandemic, revealing gaps in traditional frameworks of operations (Yamin et al., 2024). Literature on cultural dimensions of collaboration and innovation; and their synergy with AI, but empirical works missing from this space are still required to clarify this dynamic in the context of extreme disruption. To fill these gaps, research is needed to improve both theoretical insights and practical strategies for resilience in an era of unprecedented uncertainty (Ramos et al. 2023).

2.1 Organizational Culture and AI Capabilities

Organizational culture is the set of shared values, beliefs, and practices that define how a company behaves and makes decision ultimately dictating how well the company is able to adapt to technological advancements or navigate disruption. Over the last few years, however, the influence of organizational culture on AI capabilities, specifically as it relates to navigating disruptions, has been an under-theorized area of research. Rather than focusing on individual cultural parameters, the present study uses a holistic perspective on organizational culture that recognizes its influence on the outcome of AI related issues.

Collaboration, innovation and adaptability all important to AI readiness are promoted by a well-aligned organizational culture. An open & inclusive culture allows organizations to foster change adoption, collaborative thinking towards decisions, and adopt innovative technology for growth. This foster trust, shared goals coupled with the willingness to embrace the new technological solution, thus creating such a culture on which AI integration can build upon (Wong et al. 2024b).

However, when organizational cultures are inflexible and obsessed with maintaining control, it is not open to respond to disruptions or integrating AI. Cultures that prize stability, for example, may find it hard to practice the real time decision making and agility needed during crises. On the contrary, cultures that strike an appropriate balance between operational efficiency and adaptability and creativity seem better placed to leverage AI to lessen the disruption seriousness and maintain continuance during turbulent periods (Dey et al. 2024b). In this study, we extend existing literature to examine organizational culture as a unified construct that impacts AI readiness and responsiveness. (Tehrani et al. 2024) present, drawing upon institutional theory, how a solid cultural basis allows organizations to embrace AI technologies better, thereby making it easier for them to deal with external shocks and to achieve strategic goals. Other future research might probe deeper into the integration between holistic organizational culture and technological advancements so as to achieve further organizational resilience and agility.

2.2 AI Readiness and Responsiveness through the lens of Dynamic Capabilities View

Within the theoretical context of resilience, the Dynamic Capabilities View (DCV) is a critical foundation to the study of AI readiness and responsiveness. DCV argues that an organization's capacity to sense opportunities, seize them, and convert resources effectively is a key determinant of competitive edge in turbulent environments (Chaudhuri et al., 2023). This framework emphasizes the necessity of the agility and adaptability, as there traits allow AI to withstand and recover from disruptions (Riad et al. 2024). AI Readiness is a proactive type of resilience (and related to) along the lines of AI capacity to predict and ready of AI for possible disruptions. Strategic planning, resource allocation, and pre-emptive risk management together are efforts in readiness resulting in reduction of vulnerabilities in AI. AI delivered predictive analytics and real time data processing identify risks and optimize inventory before disruptions escalate (Modgil, Gupta, et al. 2022, p. 19). In addition, readiness requires knowledge management systems that are strong enough to allow for the free flow of information and collaboration among the stakeholders in order to compensate for emerging challenges (Caldarelli et al. 2021).

An opposite perspective is AI Responsiveness, which is the reactive capabilities of a AI as it relates to its ability to adapt and deprecate from disruptions after they occur. AI technologies like for real time monitoring, adaptive resource deployment and dynamic reconfiguration of AI networks are facilitating responsiveness (Riad et al.2024). For instance, crises tend to require faster decision making reckoning alongside increased precision, through the use of the AI powered automation of machine learning algorithms to enable uninterrupted AI operations (Chaudhuri et al. 2023). Despite this, there are knowledge gaps in the substantial empirical research that draws a link between these dimensions and organizational culture's contribution to resilience. It is vital to address such an intersection to progress both theoretical understanding as well as practical solutions to resilient AI management in an increasingly volatile global environment (Modgil, Singh, et al. 2022, p. 19).

2.3 Severity of disruption

A critical construct in the study of the relationship between organizational culture and how ready and prepared it is to respond to an AI disruption is a concept of disruption severity. The severity of disruption is the extent to which interruptions hamper the migration of goods, information or services through a network, define disruption severity is the magnitude and intensity of interruptions that interfere with the normal flow of organizational operations, which interferes with decision making and responses. As well as operational delays, this is a multifaceted concept, beyond financial impacts, customer dissatisfaction, and increased resource requirements, it is an important moderating variable of organizational adaptability (Ghobakhloo et al. 2023).

AI-driven contexts are particularly affected by the role of disruption severity. As AI and operational networks grow increasingly complex, the risk propagation across interdependent trade entities grows more rapid. As a result of this complexity, AI readiness is required wherein organizations integrate predictive analytics and automation to sense, plan and respond to such severe disruptions, arguing that such complexity further elongates response decision time, and, as a result, the dynamic capabilities become germane to addressing severe disruptions effectively (Nsisong Louis Eyo-Udo, 2024).

In addition, the perception-based nature of disruption severity thus complicates the management of disruption severity, as it is often possible to establish a correlation between disruption severity and perceived cost, defined by financial losses, reduced employee morale, and reduced customer satisfaction. This knowledge reinforces the necessity for high severity responsive AI systems to work in concert with organizational culture for rapid provision of timely and effective solutions (Saefullah et al. 2024).

External shocks like those that occurred in the past few months during the COVID-19 pandemic heavily reinforce the importance of organizational framework responsiveness to AI. In contrast, organizations with cultures focused on innovation and agility are far more adaptable because they use tools that harness AI to reshape resources and redefine decision-making processes during times of challenge (Hussain & Papastathopoulos 2022). Such an interaction between culture and AI capabilities is then moderated by disruption severity, suggesting its central role in driving resilience and strategic outcomes (Upadhyay et al. 2023).

3. Hypothesis Development

3.1 The Impact of Organizational Culture on AI Readiness and Responsiveness

Organizational culture (OC) is an important determinant that plays a critical role in determining the level of firm's capacity to navigate through change by exploiting new technologies. Here, if considered as a whole, it provides a central contribution to the formation of dynamic capabilities. Readiness in an organization is brought about by the organizational culture which in turn influences shared vision, staff, norms on how decisions will be made hence improving on how organizations disseminate with disruptions (El Baz et al. 2024). In the same way, it is aligned with the hierarchical stability and market-specific aim accomplishment that enhance the responsiveness of decision-making and resource integration. Research establishes that OC strengthens the implementation of AI by nurturing the common values promoting innovation and flexibility (Lissillour & Ruel 2023). Based on this understanding, we propose:

H1: Organizational culture positively impacts AI readiness
H2: Organizational culture positively impacts AI responsiveness

3.2 The Impact of Severity of Disruption on AI Readiness and Responsiveness

The intensity and unanticipated nature of disruption determine its impact on organizational priorities and resource utilization to a large extent. Severe disruptions that have been observed globally lead to an improvement in the response capacity and resilience of organizations to enable continuous business operations (Craighead et al., 2007). The authors of the existing literature show that when firms face intense disruption, they tend to rely more on prediction and pre-emptive strategies, including big data and AI approaches to managing disruptions. This alignment revives the earlier notion of The Role of Dynamic capabilities on the efficiency to manage uncertainties identified in the environment (Hosseini & Ivanov, 2022). Thus, we hypothesize:

H3: Severity of disruption has a significant impact on AI readiness
H4: Severity of disruption has a significant impact on AI responsiveness

3.3 The Moderating Role of Severity of Disruption

Moderating role of disruption severity in the relationship between OC and AI capabilities is magnifying the role of internal culture flexibility and control. High disruption enhances the congruence of OC with readiness and responsiveness with firms using cultural resources to adjust strategies and coordinate resources (Ivanov 2021). On the other hand, in a low dramatic context, OC might have a negative or even no effect on AI adoption because such situations do not put the kind of pressure on an organization to come up with new strategies as the high-drama situations do. This means that disruption severity is not only a critical parameter but forms a complex relationship with the strategic development of organizational culture for AI formation (Sherman & Roberto 2020). Therefore, we propose:

H5: Severity of disruption moderates the relationship between Organizational culture and AI readiness
H6: Severity of disruption moderates the relationship between Organizational culture and AI responsiveness

The research model is presented in Figure 1.

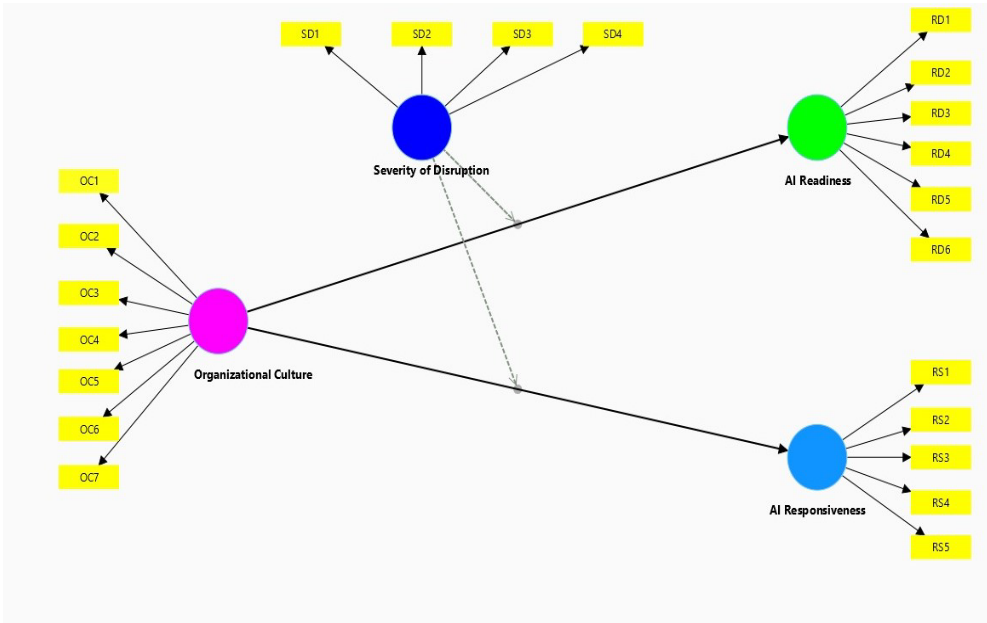

Figure 1. The Research Model

4. Methodology and Result Analysis

4.1 Data Collection and Sampling Design

This research employed a structured questionnaire to obtain responses from professionals across four key industries: IT services, Healthcare and pharmaceuticals, Manufacturing, Retail and e-commerce sub-sectors in Bangladesh. To capture a broad range of views on the state of organizational culture and AI readiness, the survey was aimed at firms of different size – from those having less than 50 employees to those with more than 5000, and age – from firms that were established less than 10 years ago to those existing more than 50 years. The targeted respondents were sent 600 survey questionnaires from which 383 valid responses were obtained such that an approximate response rate of 63.8 % was achieved.

The respondents of the present study mainly included managers, senior executives and directors who have given their perceptions and experiences about the organizational practices, culture and strategies regarding the use of AI (Tehrani et al. 2024). This questionnaire is therefore developed from previously validated constructs derived from relevant literature in order to measure the participants' perception on organizational culture, AI readiness, AI responsiveness, and disruption severity using a 5-point Likert scale ranging from 1 – strongly disagree to 5 – strongly agree as suggested by (Antony et al. 2021).In order to improve validity and reliability of the survey instrument, it was pre-tested with the other domain specialists and pilot tested on a sample of respondents. Confidentiality and anonymity of the participant as well as their voluntary consent were observed while collecting data (Dubey et al., 2022). These measures provided the best data quality that one would require for Structural Equation Modeling and Hypothesis testing. Table 1 summarizes the characteristics of the survey respondents.

Table 1. Survey Respondent Characteristics (n=383)

	Sample (n)	%
Industry		
IT Services	100	26.1
Healthcare and Pharmaceuticals	90	23.5
Manufacturing	120	31.3
Retail and E-commerce	73	19.1
Firm Size		
<50 employees	38	10
50-499 employees	96	25
500-999 employees	115	30
1000-4999 employees	96	25
>5000 employees	38	10
Firm Age (years)		
<10 years	57	15
10-19 years	76	20
20-29 years	96	25
30-49 years	96	25
>50 years	57	15
Organization's Status		
Private Company	326	85
Public Company	57	15
Respondents' Job Titles		
Manager/Executive	153	40
Senior Manager/Vice President	134	35
CEO/Director	96	25

4.2 Common Method Bias Test

Both procedural and statistical remedies are applied to address potential common method bias (CMB) in this study. The survey was designed procedurally to minimize response bias by ensuring respondent anonymity, making sure respondents would not be able to be identified by their answers, and by having respondents respond to questions in random order. Such measures lower the likelihood that respondents will give socially desirable answers or match the responses with perceptions of expectations (Mandal et al. 2022).

We then ran Harman's single factor test with all items into an unrotated principal component analysis. This indicates that minimal risk of CMB exists, as no single factor explained a majority amount of the variance. We also used a common latent factor in the structural equation model to check the lack of CMB (Fosso Wamba 2022).Finally, we address the full collinearity procedure is adopted, which consists of calculating the value of the Variance Inflation Factor (VIF) of the model's predictive constructs (El Baz et al. 2024). The results reveal that all the VIF values obtained were between 1 to 5, indicating a moderate level of multicollinearity among the predictor variables. All these results combined tell us CMB wasn't a big deal in the data we'd collected.

4.3 Measurement Model

The constructs were evaluated through the measurement model to ensure validity and reliability. Factor loadings, Cronbach's alpha, Composite Reliability (CR) and Average Variance Extracted (AVE) were used to assess convergent validity. As shown in Table 2, all factor loadings exceeded the threshold of 0.70, while CR values were greater than 0.80 and AVE more than 0.50, demonstrating robust convergent validity (Ardiyanti & Susilowati 2024). For example, the AVE and CR for AI Readiness were 0.761 and 0.945, respectively. These metrics indicated that the intended concepts were correctly measured by these constructs.

Table 2. Convergent Validity

Construct	Measurement Items	Factor Loadings	Cronbach's alpha	Composite Reliability	AVE
AI Readiness	RD1	0.824	0.937	0.945	0.761
	RD2	0.906			
	RD3	0.905			
	RD4	0.903			
	RD5	0.881			
	RD6	0.810			
AI Responsiveness	RS1	0.869	0.910	0.920	0.736
	RS2	0.880			
	RS3	0.891			
	RS4	0.888			
	RS5	0.755			
Organizational Culture	OC1	0.773	0.884	0.886	0.591
	OC2	0.829			
	OC3	0.803			
	OC4	0.818			
	OC5	0.720			
	OC6	0.705			
	OC7	0.724			
Severity of Disruption	SD1	0.811	0.839	0.892	0.675
	SD2	0.883			
	SD3	0.824			
	SD4	0.765			

We tested the discriminant validity using Heterotrait-Monotrait (HTMT) ratio. Table 3 outlines that the square roots of AVE for each construct exceeded the respective construct's correlations with other constructs, and HTMT values were less than critical threshold of 0.90, which evidenced the constructs were distinct (Manira & Effendy, 2024).

Table 3. Discriminant validity - Heterotrait-Monotrait ratio (HTMT)

	AI Readiness	AI Responsiveness	Organizational Culture	Severity of Disruption	Severity of Disruption x Organizational Culture
AI Readiness					
AI Responsiveness	0.230				
Organizational Culture	0.509	0.357			
Severity of Disruption	0.356	0.479	0.815		
Severity of Disruption x Organizational Culture	0.059	0.035	0.141	0.055	

As indicated in Table 4, Variance inflation factor (VIF) values for multicollinearity evaluation were between 1.5 to 4.5 which is well below the cut-off critical threshold of 5 and hence no serious collinearity problem is encountered. Moderate explanatory power was indicated by the R^2 values of AI Readiness (0.223) and of AI Responsiveness (0.181). Furthermore, Q^2 values of 0.204 and 0.163 validated for the predictive relevance of the model, since these values suggested robustness of the model for hypothesis testing.

Table 4. Latent Construct Coefficients

Construct	Measurement Items	VIF	R-square Co-efficients	Adjusted R-square Co-efficients	Q-square
AI Readiness	RD1	2.672	0.223	0.217	0.204
	RD2	4.043			
	RD3	4.350			
	RD4	4.376			
	RD5	3.236			
	RD6	2.239			
AI Responsiveness	RS1	2.503	0.181	0.175	0.163
	RS2	2.941			
	RS3	3.212			
	RS4	3.090			
	RS5	1.761			
Organizational Culture	OC1	2.148			
	OC2	3.312			
	OC3	3.026			
	OC4	3.293			
	OC5	3.511			
	OC6	3.352			
	OC7	1.976			
Severity of Disruption	SD1	1.822			
	SD2	2.560			
	SD3	2.066			
	SD4	1.499			

4.4 Hypotheses Testing

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to conduct the hypothesis testing due to its ability to analyze predictive models and complex dynamic relationships. The hypothesized relationships were assessed with path coefficients (β values), t-statistics and p-values, with a threshold limit of p-value < 0.05 for hypothesis acceptance.Table 5 demonstrates that the findings lend support to H1 and H2, indicating that organizational culture influence AI readiness (β = 0.40, t = 7.813, p = 0.000) and AI responsiveness (β = 0.35, t = 2.843, p = 0.004). In line with the prior studies placing organization culture at the forefront in promoting innovation as well as adaptability (Dubey et al., 2023; Tehrani et al., 2024), these findings coincide. As well, H3 and H4 were validated, such that severity of disruption had a positive and direct effect on both of AI readiness (β=0.28, t=2.618, p=0.009) and AI responsiveness (β=0.50, t=5.701, p=0.000). This corresponds with (Wong et al. 2024b) in highlighting that technological adaptation capabilities are made more effective with disruption management capabilities.

As depicted in Table 6, organizational culture was associated with moderate impact on AI readiness (β=0.22, t=2.745, p=0.006) and responsiveness (β=0.25, t=2.680, p=0.008) after controlling for disturbance in moderating their impact (H5, H6). The findings imply that organizational culture is a stronger determinant of AI capabilities at high disruptions, in line with assumptions in dynamic capability frameworks (Antony et al., 2021; Ardiyanti & Susilowati, 2024).

Table 5. Results of Hypothesis Evaluation

Hypothesis For Evaluation	Estimate	t-statistics	p-values	Outcome
Age => Organizational Culture	β=0.12	2.145	0.032	Accepted
Size => Organizational Culture	β=0.15	2.215	0.028	Accepted
Industry => Organizational Culture	β=0.18	2.305	0.041	Accepted
H1: Organizational Culture => AI Readiness	β=0.40	7.813	0.000	Accepted
H2: Organizational Culture => AI Responsiveness	β=0.35	2.843	0.004	Accepted
H3: Severity of Disruption => AI Readiness	β=0.28	2.618	0.009	Accepted
H4: Severity of Disruption => AI Responsiveness	β=0.50	5.701	0.000	Accepted

Table 6. Moderating Effect

Path	Estimate	t-statistics	p-values	Decision
H5: Severity of Disruption x Organizational Culture => AI Readiness	β=0.22	2.745	0.006	Accepted
H6: Severity of Disruption x Organizational Culture => AI Responsiveness	β=0.25	2.680	0.008	Accepted

Figure 2 illustrates the validated conceptual framework after SEM analysis, indicating all p-values < 0.05, hence the hypotheses being accepted.

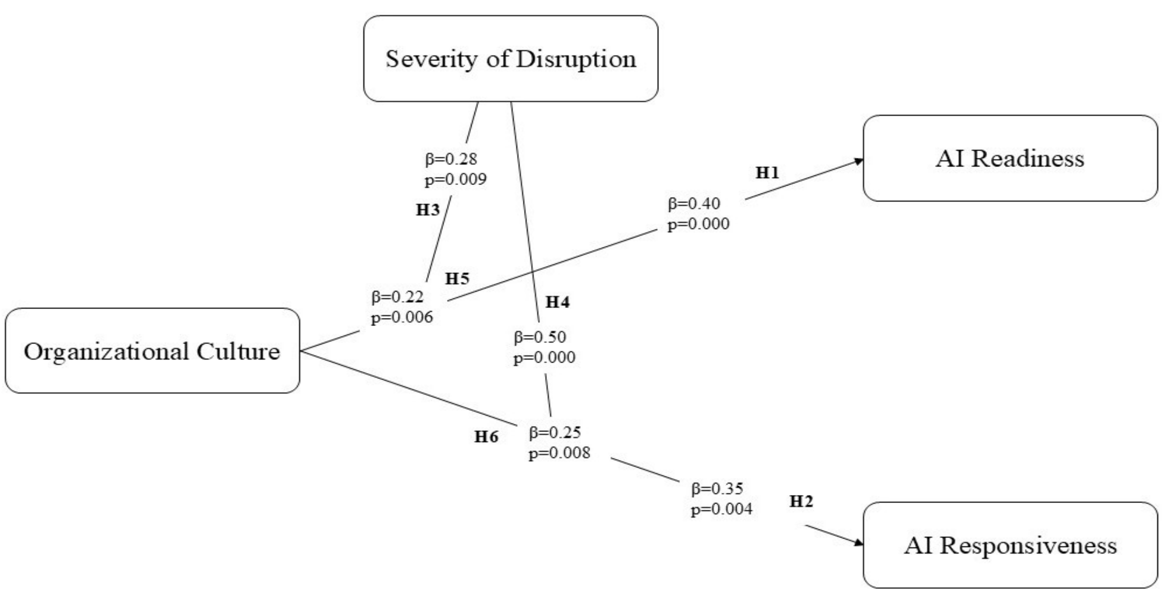

Figure 2. Final Results of Hypothesis Evaluation

5. Discussion

This investigation contributes knowledge towards the direction concerning the examination of the association in between the caliber of organizational culture, level of disruption and eagerness and flexibility towards AI. The hypothesis analyses revealed that organizational culture is a crucial determinant of the AI readiness (H1) and AI responsiveness (H2). Also, the severity of disruption was found to be an influential determinant of both AI readiness (H3) and AI responsiveness (H4). Moreover, the support for disruption severity as a moderator provided in H5 and H6 shows that it strengthens the impact of organizational culture under the conditions of high disruption scenarios. As such, these findings underscore the need to ensure that organizational cultural values are well-mapped onto external environmental conditions so that the organization can be more adaptable and ready to embrace evolving technologies during the periods of uncertainty(Martínez-Plumed et al. 2021).

Nevertheless, some limitations can be pointed out in the context of the present research. First, the cross-sectional design restricts the demonstrative temporality and potential smooth interactions. A quantitative longitudinal study in future research could produce closely related and probably more refined results. Second, this study only included four industries thus reducing the validity and generalizability of the results. It might also be possible to apply the study to other sectors and areas to increase external validity (Buettig & Stenmark, 2024). Finally, although this research operationalizes organizational culture as a whole, future work can examine cultural dimensions to investigate their modality toward the influence of AI capacities (Lee et al. 2024). Subsequent research should also consider the relationship between AI enrichment and organizational flexibility to boost the already practical knowledge and managerial approaches.

6. Conclusion

In addressing its objectives, this study offers comprehensive analysis that gives us the opportunity to understand the relationships between organizational culture, AI readiness, AI responsiveness, and disruption severity. However, our findings indicated that organizational culture is a critical enabler of AI readiness and responsiveness and a key driver of adaptability and innovation under uncertainty. This also underlines the dynamic linkage between internal organizational capabilities and the external challenges driving AI adoption, and the moderating role of disruption severity through a dynamic perspective on AI adoption strategies.

The unique contribution that this research makes is an integrated analysis of organizational culture and disruption severity, which positions these factors as central to shaping AI outcomes. This study bridges gaps in the literature and provides actionable insights to organizations that are looking to do so by proposing and validating a robust framework. This dissertation expands theoretical and practical discourses related to organizational resilience and AI integration.

References

Antony, J., Sony, M., McDermott, O., Jayaraman, R., & Flynn, D. , An exploration of organizational readiness factors for Quality 4.0: An intercontinental study and future research directions. *International Journal of Quality & Reliability Management*, *40*(2), 582–606,2021. https://doi.org/10.1108/IJQRM-10-2021-0357

Ardiyanti, A., & Susilowati, E. (2024). Perceived Usefulness and Technology Readiness Mediate Perceived Ease of Use and Digital Competence on Technology Adoption of Artificial Intelligence. *Proceedings of International Conference on Economics Business and Government Challenges*, *7*(1), Article 1. https://doi.org/10.33005/icebgc.v7i1.113

Bahrami, M., & Shokouhyar, S. ,The role of big data analytics capabilities in bolstering supply chain resilience and firm performance: A dynamic capability view. *Information Technology & People*, *35*(5), 1621–1651,2022. https://doi.org/10.1108/ITP-01-2021-0048

Bathaei, A. (2024). *Agile Supply Chains: A Comprehensive Review of Strategies and Practices for Sustainable Business Operations*.

Buettig, C., & Stenmark, J. (2024). *Unlocking AI Readiness: Navigating the Future of Purchasing and Supply Management*. https://urn.kb.se/resolve?urn=urn:nbn:se:hj:diva-64968

Caldarelli, G., Zardini, A., & Rossignoli, C. , Blockchain adoption in the fashion sustainable supply chain: Pragmatically addressing barriers. *Journal of Organizational Change Management*, *34*(2), 507–524,2021.

Chaudhuri, R., Chatterjee, S., Kraus, S., & Vrontis, D. , Assessing the AI-CRM technology capability for sustaining family businesses in times of crisis: The moderating role of strategic intent. *Journal of Family Business Management*, *13*(1), 46–67,2023. https://doi.org/10.1108/JFBM-12-2021-0153

Craighead, C. W., Blackhurst, J., Rungtusanatham, M. J., & Handfield, R. B. ,The Severity of Supply Chain Disruptions: Design Characteristics and Mitigation Capabilities. *Decision Sciences*, *38*(1), 131–156,2007. https://doi.org/10.1111/j.1540-5915.2007.00151.x

Dey, P. K., Chowdhury, S., Abadie, A., Vann Yaroson, E., & Sarkar, S., Artificial intelligence-driven supply chain resilience in Vietnamese manufacturing small- and medium-sized enterprises. *International Journal of Production Research*, *62*(15), 5417–5456,2024a. https://doi.org/10.1080/00207543.2023.2179859

Dey, P. K., Chowdhury, S., Abadie, A., Vann Yaroson, E., & Sarkar, S. (2024b). Artificial intelligence-driven supply chain resilience in Vietnamese manufacturing small- and medium-sized enterprises. *International Journal of Production Research*, *62*(15), 5417–5456. https://doi.org/10.1080/00207543.2023.2179859

Dubey, R., Bryde, D. J., Dwivedi, Y. K., Graham, G., & Foropon, C. (2022). Impact of artificial intelligence-driven big data analytics culture on agility and resilience in humanitarian supply chain: A practice-based view. *International Journal of Production Economics*, *250*, 108618. https://doi.org/10.1016/j.ijpe.2022.108618

Dubey, R., Bryde, D. J., Dwivedi, Y. K., Graham, G., Foropon, C., & Papadopoulos, T. (2023). Dynamic digital capabilities and supply chain resilience: The role of government effectiveness. *International Journal of Production Economics*, *258*, 108790. https://doi.org/10.1016/j.ijpe.2023.108790

El Baz, J., Ruel, S., Jebli, F., & Akenroy, T. (2024). The influence of organisational culture on supply chain readiness and responsiveness. *Supply Chain Forum: An International Journal*, 1–22. https://doi.org/10.1080/16258312.2024.2424151

Fosso Wamba, S. (2022). Impact of artificial intelligence assimilation on firm performance: The mediating effects of organizational agility and customer agility. *International Journal of Information Management*, *67*, 102544. https://doi.org/10.1016/j.ijinfomgt.2022.102544

Ghobakhloo, M., Asadi, S., Iranmanesh, M., Foroughi, B., Mubarak, M. F., & Yadegaridehkordi, E. (2023). Intelligent automation implementation and corporate sustainability performance: The enabling role of corporate social responsibility strategy. *Technology in Society*, *74*, 102301. https://doi.org/10.1016/j.techsoc.2023.102301

Hosseini, S., & Ivanov, D. (2022). A multi-layer Bayesian network method for supply chain disruption modelling in the wake of the COVID-19 pandemic. *International Journal of Production Research*, *60*(17), 5258–5276. https://doi.org/10.1080/00207543.2021.1953180

Hussain, M., & Papastathopoulos, A. (2022). Organizational readiness for digital financial innovation and financial resilience. *International Journal of Production Economics*, *243*, 108326. https://doi.org/10.1016/j.ijpe.2021.108326

Ivanov, D. (2021). Lean resilience: AURA (Active Usage of Resilience Assets) framework for post-COVID-19 supply chain management. *The International Journal of Logistics Management*, *33*(4), 1196–1217. https://doi.org/10.1108/IJLM-11-2020-0448

Lee, A., Shankararaman, V., & Eng Lieh, O. (2024). Enhancing citizen service management through AI-enabled systems—A proposed AI readiness framework for the public sector. In Y. Charalabidis, R. Medaglia, & C. Van Noordt (Eds.), *Research Handbook on Public Management and Artificial Intelligence* (pp. 79–96). Edward Elgar Publishing. https://doi.org/10.4337/9781802207347.00014

Lissillour, R., & Ruel, S. (2023). Chinese social media for informal knowledge sharing in the supply chain. *Supply Chain Forum: An International Journal*, *24*(4), 443–461. https://doi.org/10.1080/16258312.2022.2130006

Mandal, S., Kavala, H. B., & Potlapally, G. D. (2022). Does Organizational Culture Matter for Shaping up Hotel's Responsiveness to Customer's Demand? An Empirical Investigation. *International Journal of Hospitality & Tourism Administration*, *23*(2), 190–215. https://doi.org/10.1080/15256480.2020.1727811

Manira, S., & Effendy, L. (2024). The Influence of Technological Knowledge and Digital Skills on Accounting Students' Readiness to Face Artificial Intelligence Technology. *International Journal of Management, Accounting & Economics*, *11*(5), 581–598. https://doi.org/10.5281/zenodo.11311900

Martínez-Plumed, F., Gómez, E., & Hernández-Orallo, J. (2021). Futures of artificial intelligence through technology readiness levels. *Telematics and Informatics*, *58*, 101525. https://doi.org/10.1016/j.tele.2020.101525

Modgil, S., Gupta, S., Stekelorum, R., & Laguir, I. (2022). AI technologies and their impact on supply chain resilience during COVID-19. *International Journal of Physical Distribution & Logistics Management*, *52*(2), 130–149. https://doi.org/10.1108/IJPDLM-12-2020-0434

Modgil, S., Singh, R. K., & Hannibal, C. (2022). Artificial intelligence for supply chain resilience: Learning from Covid-19. *The International Journal of Logistics Management*, *33*(4), 1246–1268. https://doi.org/10.1108/IJLM-02-2021-0094

Nsisong Louis Eyo-Udo. (2024). Leveraging artificial intelligence for enhanced supply chain optimization. *Open Access Research Journal of Multidisciplinary Studies*, *7*(2), 001–015. https://doi.org/10.53022/oarjms.2024.7.2.0044

Ramos, E., Patrucco, A. S., & Chavez, M. (2023). Dynamic capabilities in the "new normal": A study of organizational flexibility, integration and agility in the Peruvian coffee supply chain. *Supply Chain Management: An International Journal*, *28*(1), 55–73. https://doi.org/10.1108/SCM-12-2020-0620

Riad, M., Naimi, M., & Okar, C. (2024). Enhancing Supply Chain Resilience Through Artificial Intelligence: Developing a Comprehensive Conceptual Framework for AI Implementation and Supply Chain Optimization. *Logistics*, *8*(4), 111. https://doi.org/10.3390/logistics8040111

Saefullah, E., Suseno, B. D., & Rohaeni, N. (2024). Navigating uncertainty: The interplay of future job forecasting, learning agility, responsiveness, and adaptability. *Journal of Infrastructure, Policy and Development*, *8*(12), 8845. https://doi.org/10.24294/jipd.v8i12.8845

Sherman, W. S., & Roberto, K. J. (2020). Are you talkin' to me?: The role of culture in crisis management sensemaking. *Management Decision*, *58*(10), 2195–2211. https://doi.org/10.1108/MD-08-2020-1017

Tehrani, A. N., Ray, S., Roy, S. K., Gruner, R. L., & Appio, F. P. (2024). Decoding AI readiness: An in-depth analysis of key dimensions in multinational corporations. *Technovation*, *131*, 102948. https://doi.org/10.1016/j.technovation.2023.102948

Ul Akram, M., Islam, N., Chauhan, C., & Zafar Yaqub, M. (2024). Resilience and agility in sustainable supply chains: A relational and dynamic capabilities view. *Journal of Business Research*, *183*, 114855. https://doi.org/10.1016/j.jbusres.2024.114855

Upadhyay, N., Upadhyay, S., Al-Debei, M. M., Baabdullah, A. M., & Dwivedi, Y. K. (2023). The influence of digital entrepreneurship and entrepreneurial orientation on intention of family businesses to adopt artificial intelligence: Examining the mediating role of business innovativeness. *International Journal of Entrepreneurial Behavior & Research*, *29*(1), 80–115. https://doi.org/10.1108/IJEBR-02-2022-0154

Wong, L.-W., Tan, G. W.-H., Ooi, K.-B., Lin, B., & Dwivedi, Y. K. (2024a). Artificial intelligence-driven risk management for enhancing supply chain agility: A deep-learning-based dual-stage PLS-SEM-ANN analysis. *International Journal of Production Research*, *62*(15), 5535–5555. https://doi.org/10.1080/00207543.2022.2063089

Wong, L.-W., Tan, G. W.-H., Ooi, K.-B., Lin, B., & Dwivedi, Y. K. (2024b). Artificial intelligence-driven risk management for enhancing supply chain agility: A deep-learning-based dual-stage PLS-SEM-ANN analysis. *International Journal of Production Research*, *62*(15), 5535–5555. https://doi.org/10.1080/00207543.2022.2063089

Yamin, M. A., Almuteri, S. D., Bogari, K. J., & Ashi, A. K. (2024). The Influence of Strategic Human Resource Management and Artificial Intelligence in Determining Supply Chain Agility and Supply Chain Resilience. *Sustainability*, *16*(7), 2688. https://doi.org/10.3390/su16072688

Biographies

Nasif Morshed is an aspiring undergraduate student currently pursuing a B.Sc. Engineering degree in Industrial and Production Engineering (IPE) from Khulna University of Engineering and Technology. His research interests include Supply Chain Management, Operations Research and Machine Learning, with a focus on their interdisciplinary applications.

Mushfiqur Rahman is an ambitious undergraduate student currently pursuing a B.Sc. Engineering degree in Industrial and Production Engineering (IPE) from Khulna University of Engineering and Technology. His research interests include Supply Chain Management, Machine Learning and Materials Science.

Kazi Md. Tanvir Anzum received B.Sc. Engineering degree in Industrial and Production Engineering from Khulna University of Engineering and Technology. His research interests include Supply Chain management, Operations Research, Lean manufacturing. He is a lecturer at Department of Industrial Engineering and Management at Khulna University of Engineering and Technology, Khulna, Bangladesh.
Orcid Id: https://orcid.org/0009-0009-7422-350X