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Barriers to Artificial Intelligence Adoption in Retail: An Integrated TISM Approach

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Abstract

The retail sector is getting transformed through, artificial intelligence through data driven decision making, enhanced operational efficiency and customer experience. Despite huge potential, AI adoption in retail is uneven due to various interrelated barriers. This research aims to examine these barriers, and structure using Total Interpretive Structural Modelling. The barriers to AI adoption were first identified from literature followed by validation from the panel of experts. TISM was implemented, to establish hierarchical relationships among the barriers, and provide interpretive insights for these relationships. The results suggest that lack of top management support, and absence of a clear AI strategy are the most critical driving barriers, influencing technological, data-related, and organizational constraints, which lead to resistance to change, and misalignment of business goals. The findings offer a structured framework, contributing towards understanding AI adoption barriers and insights for practioners.

Keywords: *Artificial Intelligence, Retail, TISM, Barriers, Technology Adoption*

I. INTRODUCTION

Artificial Intelligence is modifying the retail sector by enhancing the capabilities, such as personalized customer experiences, predictive analytics, and intelligent supply chain management. Retailers are leveraging, AI driven technologies for demand forecasting, recommendation systems, and automated service delivery, thereby enhancing efficiency and competitiveness (Davenport et al., 2023; Verhoef et al., 2021). With digital transformation, customers are expected to not return to traditional buying (Sharma et. al., 2022; Sharma et. al., 2023). Today, firms and customers connect without physical interaction (Sharma & Dwivedi 2022). With the rapid expansion of digital and omnichannel retailing, AI has become a strategic necessity rather than a technological option (Cui & Bulis, 2025; MDPI, 2024). Despite its recognized potential, the adoption of AI in retail remains uneven, with many organizations struggling to move beyond pilot initiatives to large-scale implementation (Dwivedi et al., 2023). Existing literature indicates that AI adoption is constrained by multiple interrelated barriers, including technological limitations, data challenges, organizational constraints, financial concerns, and ethical issues (Vėželis & Gopal, 2024; Kane et al., 2019; Martin et al., 2020). Previous studies have identified these barriers, but they majorly examine them in isolation, offering limited insight into their interdependencies and hierarchical relationships. This fragmented understanding restricts the ability of both researchers and practitioners to identify the most critical driving and dependent barriers influencing AI adoption in retail. There is a need for a structured approach, that can systematically model the complex relationships among these barriers. For addressing this gap, current research employs total interpretive structured modelling to identify and analyse, the hierarchical structure of barriers to AI adoption in the retail sector. TISM is particularly, suitable for examining complex systems as it enables the classification of factors into different levels based on their driving and dependence power. By implementing TISM, the present study aims to develop a structured framework that highlights the key driving barriers and their impact on other constraints. The results are expected to provide both theoretical contributions by advancing the understanding of barrier interrelationships and practical implications by supporting retail managers prioritize interventions for effective AI adoption.

II. LITERATURE REVIEW

Artificial Intelligence has been a transformative force in retail sector, enabling advanced personalization, predictive analytics, and operational efficiency across customer engagement, inventory management, and demand forecasting (Cui & Bulis, 2025; MDPI, 2024; Davenport et al., 2023). But AI adoption remains uneven, reflecting a persistent gap between technological potential and actual implementation. This disconnect has been examined through the Technology Organization Environment (TOE) framework and the Technology Acceptance Model (TAM), which explain the combined role of technological readiness, organizational capability, and user perception (Tornatzky & Fleischer, 1990; Davis, 1989). The new technology development has created highly competitive market conditions (Sharma, M 2017) but also positive customer experience, which leads to more enhanced satisfied customers(Chandok and Gupta 2014). Existing literature adopts fragmented approaches, failing to integrate these perspectives. Technological barriers such as legacy systems, integration complexity, and inadequate infrastructure continue to constrain adoption (Vėželis & Gopal, 2024; Dwivedi et al., 2023), while data driven challenges including fragmented architectures, poor governance, and privacy concerns reduce AI effectiveness and negatively impact perceived usefulness, and ease of use (MDPI, 2024; Rai et al., 2022; Venkatesh et al., 2003; Adanyin, 2024; Martin et al., 2020). These challenges are often treated as isolated technical constraints, revealing a key research gap to understand their interdependent and behavioural implications within the retail sector.

At the organizational levels these barriers like, lack of skilled workforce, resistance to change, and weak leadership support further obstruct AI adoption (Vėželis & Gopal, 2024; Kane et al., 2019; Verhoef et al., 2021). Employee related concerns, including fear of job displacement, lack of trust, and innovation resistance also significantly influence adoption outcomes, with recent evidence identifying innovation resistance as a critical mediator in retail AI implementation (Venkatesh et al., 2003; Jussupow et al., 2021). Additionally, financial constraints such as high implementation costs and uncertain return on investment (ROI) limit adoption, particularly among SMEs (Bughin et al., 2018; TechRadar, 2026), while ethical and regulatory concerns related to bias, transparency, and data protection further complicate decision-making (Martin et al., 2020; Dwivedi et al., 2023; Technological Forecasting and Social Change, 2024). Despite the identification of these barriers, the literature lacks retail specific integrated models which combine technological, organizational, behavioural, financial, and ethical dimensions within a unified TOE TAM framework. This fragmentation identifies a critical research gap which suggests a need for an integrated holistic approach to explain, and predict AI adoption in retail.

III. RESEARCH METHODOLOGY

The study adopts exploratory research design using total interpretive structural modelling to analyse the interrelationships among barriers of AI adoption in the retail industry. ISM is an established way to structure the complex issues and develop hierarchical model by examining relationships among variables (J. Warfield, 1974). To improve interpretability, the research uses Total Interpretive Structural Modelling, incorporating interpretive logic for each relationship.

First the key barriers to AI adoption in retail were identified by comprehensive literature review followed by validation from a panel of 7 academicians and 8 retail and AI practioners to refine the barrier list. Further pairwise relationships among the barriers were established using symbols as below.

1. V : i influences j
2. A : j influences i
3. X : mutual influence
4. : no relation

A reachability matrix was created by converting a Structural Self-Interaction Matrix (SSIM). The hierarchical model was constructed using level partitioning. Each link is explained with contextual reasoning to enhance theoretical contribution. Lastly, the barriers were categorized according to driving and dependence power using MICMAC analysis

IV. ANALYSIS AND RESULTS

15 barriers were identified and were then coded as mentioned in the list below:

Table 1: Barrier Coding

Code	Barrier
R1	“Legacy systems”

R2	“Integration complexity”	R9	“Lack of top management support”
R3	“Scalability issues”	R10	“High implementation cost”
R4	“Poor data quality”	R11	“Uncertain ROI”
R5	“Data silos”	R12	“Algorithmic bias”
R6	“Data privacy concerns”	R13	“Regulatory issues”
R7	“Lack of skilled workforce”	R14	“Lack of AI strategy”
R8	“Resistance to change”	R15	“Misalignment with business goals”

TABLE 2: SSIM (STRUCTURAL SELF INTERACTION MATRIX)

	R1	**R2**	**R3**	**R4**	**R5**	**R6**	**R7**	**R8**	**R9**	**R10**	**R11**	**R12**	**R13**	**R14**	**R15**
R1	_	V	V	O	O	O	O	O	A	O	O	O	O	A	A
R2		_	V	V	V	O	O	O	A	O	O	O	O	A	A
R3			_	V	V	O	O	O	A	O	O	O	O	A	A
R4				_	V	V	O	O	O	O	O	O	O	A	A
R5					_	V	O	O	O	O	O	O	O	A	A
R6						_	O	O	O	O	O	V	V	O	O
R7							_	V	A	O	O	O	O	A	A
R8								_	O	O	O	O	O	O	A
R9									_	V	V	O	O	V	V
R10										_	V	O	O	V	V
R11											_	O	O	V	V
R12												_	V	O	O
R13													_	O	O
R14														_	V
R15															_

Table 3: Initial Reachability Matrix (Binary Conversion)

Rules applied: V for (1,0), A for (0,1), X for (1,1), O for (0,0).

	R1	**R2**	**R3**	**R4**	**R5**	**R6**	**R7**	**R8**	**R9**	**R10**	**R11**	**R12**	**R13**	**R14**	**R15**
R1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
R2	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0
R3	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0
R4	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
R5	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0
R6	0	0	0	0	0	1	0	0	0	0	0	1	1	0	0
R7	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0
R8	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0

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R9	0	0	0	0	0	0	1	0	1	1	1	0	0	1	1
R10	0	0	0	0	0	0	0	0	0	1	1	0	0	1	1
R11	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1
R12	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
R13	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
R14	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
R15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Table 4: Final Reachability Matrix

	R1	**R2**	**R3**	**R4**	**R5**	**R6**	**R7**	**R8**	**R9**	**R10**	**R11**	**R12**	**R13**	**R14**	**R15**
R1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
R2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
R3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
R4	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
R5	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
R6	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
R7	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
R8	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
R9	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
R10	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
R11	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
R12	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
R13	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
R14	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
R15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

	R1	**R2**	**R3**	**R4**	**R5**	**R6**	**R7**	**R8**	**R9**	**R10**	**R11**	**R12**	**R13**	**R14**	**R15**
R1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
R2	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0
R3	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0
R4	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
R5	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0
R6	0	0	0	0	0	1	0	0	0	0	0	1	1	0	0
R7	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0
R8	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
R9	0	0	0	0	0	0	1	1	1	1	1	0	0	1	1
R10	0	0	0	0	0	0	0	0	0	1	1	0	0	1	1
R11	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1
R12	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
R13	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
R14	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
R15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

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Table 5: ISM Levels

Level	Barrier Code	Barrier Description
Level I	R8	Resistance to change
Level I	R15	Misalignment with business goals
Level II	R7	Lack of skilled workforce
Level II	R11	Uncertain ROI
Level III	R4	Poor data quality
Level III	R5	Data silos
Level III	R2	Integration complexity
Level IV	R1	Legacy systems
Level IV	R3	Scalability issues
Level IV	R10	High implementation cost
Level V	R9	Lack of top management support
Level V	R14	Lack of (AI) strategy
External	R12	Algorithmic bias
External	R13	Regulatory issues

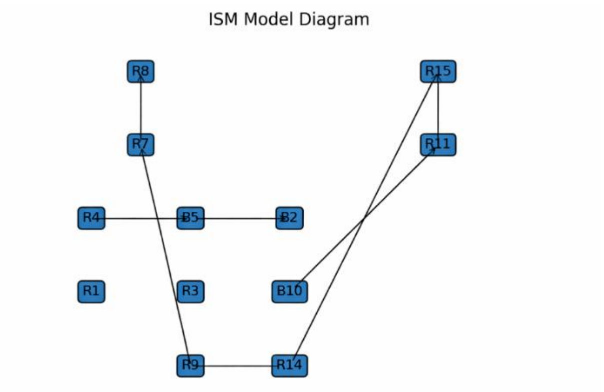

Figure 1: The TISM Model

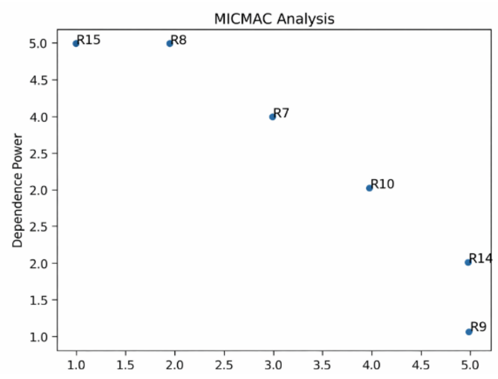

Figure 2: MICMAC Analysis

Table 2 presents SSIM analysis inferring that leadership and strategic barriers are the primary drivers, technological and data related barriers form interrelated intermediate layers, while behavioral barriers come out as dependent outcomes, reflecting the complex and hierarchical behaviour of AI adoption challenges in retail sector. As shown in table 3, the initial reachability matrix reveals a falling structure in which leadership and strategic barriers drive technological and operational challenges, leading to behavioural resistance and misalignment, which prominently highlights the hierarchal structure of AI adoption barriers in retail.

Table 4 represents the final reachability matrix infers a hierarchical structure where leadership and strategic barriers are the primary drivers, technological and data-related barriers form intermediate linkages, and behavioural barriers emerge as dependent outcomes, highlighting the descending and interdependent nature of AI adoption barriers in retail.

In figure 1, the TISM model represents that leadership and strategic barriers act as primary drivers, which flow through technological and operational barriers resulting in behavioural resistance and strategic misalignment towards AI adoption in the retail sector.

The MICMAC analysis in figure 2 interprets that leadership and strategic barriers form the driving forces, whereas technological and operational barriers are the linkage variables, while behavioural resistance become the dependent outcome, contributing towards systematic and interdependent nature of AI adoption barriers in retail industry.

V. FINDINGS, IMPLICATIONS AND SUGGESTIONS

The analysis infers a multi level hierarchical structure of barriers. At the, lower level lack of top management support and absence of AI strategy, behave as the key driving barriers which influence various intermediate barriers, like skills gap, data issues and integration complexity. Barriers like poor data quality, data silos and integration challenges in the middle level act as linkage variables. These barriers being unstable, as they influence and get influenced by other factors. Resistance to change and misalignment with business goals, being at the highest level emerge as dependent barriers, presenting the outcomes of underlying structural challenges. The TISM interpretation further explains these relationships, like the lack of top management support leads to weak AI strategy as leadership defines organizational preferences. Poor data quality impacts AI adoption as algorithms depends on accurate data inputs. The results explain the dropping nature of barriers, working on this root causes can reduce the downstream challenges. This study explains that the barriers to AI adoption in retail, are hierarchical and interdependent. By using TISM, the research provides, a structured understanding of these barriers and their relationships. This research contributes significantly towards, the existing literature on artificial intelligence adoption in retail. At first it provides integrated and holistic framework, to understand the barriers by identifying and systematically, structuring them with the help of TISM approach. Next it extends, the application of TISM with the context of retail, which is found unexplored in the existing literature. Third the research explains, the interdependent and hierarchal nature of AI adoption barriers, focusing on foundational drivers influencing intermediate and dependent barriers, showing declining behaviour. Lastly the model contributes, by integrating financial, technological, organizational and ethical dimensions into a structured analytical framework by explaining, the complexities with adoption in retail. The findings provide valuable insights for practioners, like organizations need to prioritize top management commitment as leadership support, is found as the most critical driver influencing other barriers. The managers and practioners, need to build clear and well defined AI strategy aligning organizational goals with resource allocation. Also, retailers need to organize skill development programs addressing the workforce related challenges and reduce resistance to change. Attention is required to improve data quality, integration and infrastructure to enhance the effectiveness of AI systems in retail sector. Together, these measures can help organizations systematically, overcome barriers and improve AI adoption outcomes.

VI. LIMITATIONS AND FUTURE SCOPE

The results emphasize, the importance of addressing foundational issues, such as leadership support and strategic alignment to ensure successful AI adoption. There are certain limitations also, which need to be addressed. At first the analysis relies on judgement of experts, which may lead to potential biasness, while defining relationships among the barriers, then the small sample size of experts may restrict generalizability of findings across different contexts. Then the model, being retail specific cannot be applicable directly to other industries. These limitations provide important directions, for further refinement, and validation of the model. Working on these limitations, will emerge several avenues for future research. Future researchers can apply, structured equation modelling to statistically validate, the relationships identified through TISM framework. There is scope to explore industry specific variations, to enhance the implication of model, in different sectors. Further hybrid modelling techniques, can enhance robustness and generalizability of the findings.

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For papers published in translation journals, please give the English citation first, followed by the original foreign-language citation [6].

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