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Artificial intelligence and machine learning adoption in automotive organizations using technology-organization-environment framework

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Abstract

Purpose: This research purposes to give a thorough knowledge of the factors impacting the adoption of AI/ML in demand forecast management within automotive organizations. In automotive organizations, artificial intelligence technology and machine learning algorithms (AI/ML) can increase demand forecast accuracy, time series forecasting, predictive analytics, inventory management, production planning, and supply chain efficiency.

Methodology: Built on the Technology-Organization-Environment underpinning theory, this study validates the AI/ML adoption intentions. In this empirical study, primary data from 257 employees of small, medium, and big automotive organization was used to test a conceptual model using structural equation modelling.

Findings: Technology factors such as AI/ML complexity and innovation, organizational factors like internal policies, organization communication, and data integrity, and environmental factors like government regulations and economic conditions were favourable for AI/ML adoption in automotive industries. The results highlight that organizational capability, AI/ML compatibility and localization were insignificant in the context of demand forecasting.

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Implications: This study provides theoretical and practical implications as Automotive organizations may respond swiftly to dynamic settings by using AI/ML to quickly adjust to shifting market conditions, customer preferences, and unanticipated demand variations.

Subject Classification: *62P25, 91B15, 91B55.*

Keywords: *Artificial intelligence, Machine learning, Automobile industry, Demand forecasting, Technology-organization-environment framework.*

1. Introduction

Artificial intelligence technology and Machine Learning algorithms (AI/ML) have drastically changed various business domains. However, they are mighty in the Automobile industry. The automobile industry plays a significant role in the growth of the country's economic condition [1]. Automative industry has witnessed lots of transformations by adopting technology to increase productivity through enterprise resource planning [2]. The industry's economic growth is reflected in producing goods and services that provide transportation infrastructure and increase vehicle sales. There is always a scope for enhancement in the automobile industry, and AI and ML will meet the customers' increasing demand [3]. Technology adoption at organizations has challenges [4]. There are studies that explored the impact of disruptions on automobile sector growth [5] and AI/ML readiness of small and medium enterprises [6].

The use of these techniques vastly helps in drawing great insights from the raw dataset. Predicting the complexity of these techniques in the real world is very uncertain. AI-enabled chips are intelligent enough to enable cars to operate on electricity and navigate through roads, traffic, congested areas, unclear routes, and traffic signals [7]. Artificial intelligence (AI) is used in today's systems as the fundamental key to assisting automated driving processes. Its functions help clients park, drive safely, navigate, and stay in touch. It can take control of the steering for extended periods, but the driver still needs to be present to track what is happening. The special assistant allows the car to be controlled and accessed only using voice commands. [7]

Demand forecasting is vital for strategic planning. Demand forecasting predicts future trends for a particular subject based on a specific industry's current trajectory and happenings. It will help automobile companies predict future market trends and make informed decisions about production and distribution [8] AI and ML features implemented in automobiles are lane-changing assistance, adaptive cruise control, voice recognition, and self-driving. Unsupervised learning alerts the user of unprecedented events to ensure their safety and avert the risk of fatal accidents and consequences. Machine learning is the best method for AI systems to train and improve.

We will use Partial Least Square [PLS] for our research, which includes empirical study. It is beneficial when we must predict a set of dependent variables from a large set of independent variables [9]. We aim to analyze the adoption of Artificial Intelligence technology and Machine Learning techniques in automotive organizations. The improper utilization of finances, human labour, and resources, incompatibility of integration and updating of rules and regulations to the products released in the market, user and data security, environmental implications, and techniques used for manufacturing and testing motivated us to pursue our research. Questions that will be addressed in our research are as follows:

What are the significant factors that impact the adoption of AI/ML for Demand forecast management in Automotive Organizations?

The study objectives mentioned are

- To create a model to verify the factors influencing adoption of Artificial Intelligence and Machine Learning techniques for Demand forecast management in Automotive Organizations.
- To investigate the impact of technological, organizational and environmental factors of AI/ML adoption.

Literature Review

In this section we give an overview of the significance of the proposed theory. We further explained the conceptual framework/model created and developed the study hypotheses.

Theory – Technology-Organization-Environment

TOE framework is used to analyze and understand the factors prompting the adoption and usage of technological innovations within industries/organizations. [10] It provides a structured approach for examining how internal organizational structures, external environmental conditions, and the specific characteristics of the technology itself shape technology-related decisions. The TOE framework acknowledges that technology is a crucial element in the innovation process, and it examines how specific characteristics of technology impact an organization's willingness and ability to adopt and integrate innovations. [11] The technology factors include vehicles power by electricity, autonomous and remote monitory systems, collaborative robots, drones and connected vehicle technologies.

The Organization Factor refers to the firm's size, scope of operations, technological knowhow, structures and capabilities which impact the ability to effectively plan, consider, implement technology innovations. Being an integral part of the TOE framework, these factors can augment researchers to investigate possible implementation concerns, revise internal policies, restructure their internal structures, and create strategies to successfully adopt innovative technologies. The Environment factors include market demands, industry trends, regulatory requirements, industry norms, economic conditions, social attitudes, competitive pressures, and other external factors that shape the organization's environment. [12]

Conceptual framework and hypothesis formulation

We developed the conceptual framework in figure 1 based on above theory.

AI/ML technology increases the complexity factor in the automobile industry. The automotive supply chains are complex, with many stakeholders involved. Hence, reliable demand modelling and forecasting requires complex AI and ML technologies. [11]

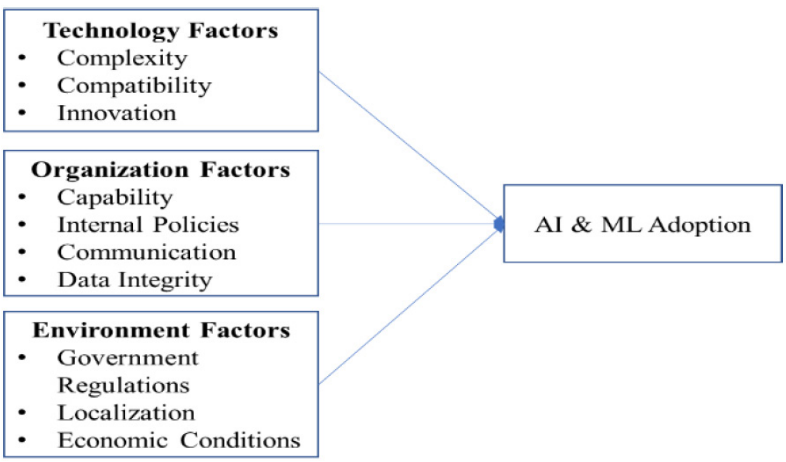

Figure 1

The conceptual framework for AI/ML adoption

H1: The Complexity of technology has negative impact on adoption of AI and ML in automobile industry.

The adoption of AI and ML technologies enhances the compatibility factor in the automobile industry and should have the potential that it should match the various components, systems, and customer responses. [12]

H2: The compatibility of technology has positive impact on adoption of AI and ML in automobile industry.

Firms that support an open innovative culture are more likely to implement AI & ML in their decision-making process. Innovative environment in the workplace encourages employees to explore and apply state-of -the-art solutions, which in turn enables integrating AI in a wide range of automotive applications such as predictive maintenances, spare parts management and simulating autonomous driving experience. [13]

H3: Technological innovation impacts the adoption of Artificial Intelligence (AI) Machine Learning (ML) in the various processes of the automobile industry.

An organization's capability is represented by its strategic alliances, technical know-how, adaptability, regulatory and statutory compliance and financial stability. These factors significantly impact the applications of AI & ML for the critical processes of the automobile industry [14].

H4: The organizational capability will positively impact the application of AI and ML in the Automobile Industry processes.

Organization policies are important to determine the effectiveness of how AI and ML applications are used are not only productive, but also responsible and ethical. The usefulness of AI/ML integration into the core processes of the company will be governed by the policies. In other words, the policies guide the efficient usage of AI and ML applications within the organization and impact its culture.

H5: Internal policies of the organization impact the adoption of AI and ML applications in select processes of the automobile industry.

Open and transformation flow of communication is a vital component while applying AI and ML for organizational decision-making. Employees should have easy access to information, issue management, suggestions management. This kind of communication guarantees that objectives are in line, promotes teamwork, effectively handles change, informs stakeholders, and fosters trust. [15]

H6: Communication in the organization has an impact on adoption of AI and ML in automobile industry.

The efficiency of robust security measures that ensure the integrity of data collected in the automotive industry can lead to more accurate and reliable information. This improved data integrity can result in enhanced operational efficiency, as decisions based on trustworthy data resulting in a significant positive impact on overall industry productivity. [16]

H7: There will be a positive impact of the Data Security on the use of AI and ML in automobile industry.

As governments and regulatory bodies increasingly focus on data protection and privacy, implementing robust security measures can position the automotive industry for compliance with evolving legal requirements. [12]

H8: There is a significant impact of regulations of the Government on the use of AI and ML

Regulations and standards for the automotive sector vary by location and are influenced by specific cultural preferences. By ensuring that AI technologies in the automotive sector are appropriately adapted to the distinctive features of various locations, effective localization promotes wider acceptance and integration into a variety of markets. [17]

H9: There is significant impact of localization on the adoption of AI-ML

In a favorable economic environment, automotive companies are more likely to invest in and adopt AI and ML technologies to enhance vehicle features, optimize manufacturing processes, and improve overall operational efficiency, thereby fostering innovation within the industry. [18]

H10: There is significant impact of Economic Condition on the adoption of AI-ML

Research Methodology

Surveys data were used to validate the conceptual framework and the formulated hypotheses. It was necessary to construct a questionnaire for this. Constructs are identified based on theory and the literature review. All of the items that represented the constructs chosen for the suggested study model were used to develop the questionnaire.

Measures

Research constructs were measured using items from earlier studies. Four items each for Technology complexity (CPLEX), technology compatibility (COMPAT), and technology innovation (INNO) [19], and organization capability (CAP), internal policies (POL), organization communication (COMM), Organization data integrity (DAIN) [20], [21], [22], government regulations (REG), localization (LOC), economic conditions (ECO) [23], and AI/ML adoption (ADOP) [24] were adjusted to measure factors/constructs using seven-point Likert scale.

Data collection and analysis

The minimum required sample size was calculated using the G*Power analysis tool. [25] Purposive sampling facilitated the employee selection of Top- and middle-level positions of automotive organizations where AI/ML is being adopted. Practically, we targeted automotive organizations from the Maratha Chamber of Commerce Industries and Agriculture (MCCIA)(India). We targeted 300 organizations, out of which 162 industries were inclined towards adopting or were undergoing the process. Among these 162 organizations, we were able to gather contact details for 257 employees. Table 1 shows the demographic distribution of the employees. The Smart PLS 4.0 l was used to analyze primary data through structural equation modelling. [26]

Table 1

Respondent profile

Items	Category	Count	Frequency
Gender	Male	142	55.25%
	Female	115	44.75%
Designation	Owners/Proprietors	35	13.62%
	IT Managers	59	22.96%
	Functional Managers	163	63.42%
Category of enterprise	Small	57	22.18%
	Medium	143	55.64%
	Large	57	22.18%

Measurement model evaluation

The internal consistency measured through the composite reliability (CR), the validity of all constructs calculated over average variance extracted (AVE), multicollinearity check using variance inflation factor (VIF), constructs' consistency was checked by Cronbach's alpha (α). All the valuations are shown in Table 2. Discriminant validity was checked implementing the Fornell and Larker's [27] criteria in Table 2.

Table 2
Construct Reliability and Validity

Constructs	CPLEX	COMPAT	INN	CAP	POL	COMM	DAIN	REG	LOC	ECO	ADOP	Cronbach's alpha	CR	AVE
(CPLEX)	0.797											0.881	0.885	0.635
(COMPAT)	0.386	**0.890**										0.868	0.869	0.792
(INN)	0.497	0.589	**0.827**									0.867	0.870	0.685
(CAP)	0.439	0.342	0.721	**0.860**								0.936	0.938	0.740
(POL)	0.308	0.514	0.698	0.726	**0.797**							0.909	0.911	0.635
(COMM)	0.210	0.473	0.763	0.740	0.674	**0.890**						0.902	0.904	0.793
(DAIN)	0.411	0.346	0.615	0.663	0.705	0.568	**0.857**					0.859	0.867	0.734
(REG)	0.373	0.662	0.650	0.708	0.675	0.638	0.590	**0.846**				0.866	0.881	0.716
(LOC)	0.453	0.404	0.450	0.547	0.482	0.467	0.406	0.682	**0.934**			0.727	0.927	0.872
(ECO)	0.253	0.404	0.150	0.275	0.182	0.367	0.206	0.382	0.235	**0.884**		0.703	0.893	0.782
(ADOP)	0.424	0.350	0.575	0.162	0.267	0.206	0.388	0.287	0.432	0.547	**0.871**	0.823	0.874	0.759

Structural model and hypothesis testing

Standardized hypotheses path coefficients (β value), significance level, and R2 estimates were calculated to check the structural model. [26] R-square adjusted values for dependent constructs were, calculated, explaining the variation of 65.1% for AI/ML adoption. As shown in Table 3, all hypothesized relationships are evaluated

Discussion

Here, we discuss the implications theoretically and practically. Technological, organizational, and environmental characteristics have an impact on the adoption of AI/ML technologies. The results gave us significant observations about the adoption of AI and ML in the Automobile Organization. The percentage of explained variance (R2) for AI/ML adoption is 65.1%. suggesting that the structural model has predictive relevance. All beta coefficients were accessed as shown in Table 3.

Table 3

Hypothesis relationship

Hypotheses	Relationship	Value β	t statistic	p values	Decision
H1a	CPLEX -> ADOP	-0.171	4.191	0.000	Accepted
H1b	COMPAT -> ADOP	0.045	0.648	0.487	Rejected
H1c	INN -> ADOP	0.496	8.020	0.000	Accepted
H2a	CAP -> ADOP	0.173	1.598	0.090	Rejected
H2b	POL -> ADOP	0.308	5.511	0.001	Accepted
H2c	COMM-> ADOP	0.496	8.020	0.000	Accepted
H2d	DAIN -> ADOP	0.210	3.083	0.002	Accepted
H3a	REG -> ADOP	0.281	3.709	0.000	Accepted
H3b	LOC -> ADOP	0.147	0.865	0.062	Rejected
H3c	ECO-> ADOP	0.262	3.044	0.000	Accepted

H1a and H1c suggest that technology factors like perceived complexity ($\beta = -0.171$, $p < 0.05$) and innovation ($\beta = 0.496$, $p < 0.05$) have a significant influence on AI/ML adoption, were supported. Technical expertise and abilities to comprehend, implement, and manage complex AI/ML systems for performance improvements is essential for adoption. Organizations have to train the employees on technology disruptions to facilitate smooth adoption. H2b, H2c, and H2d suggest organizational factors like internal policies ($\beta = 0.308$, $p < 0.05$), communication ($\beta = 0.496$, $p < 0.05$) and data integrity ($\beta = 0.210$, $p < 0.05$) have a positive influence on AI/ML adoption. Data governance policies, ethical guidelines, with effective stakeholder engagement is significant for AI/ML adoption. Organizations have to ensure data integrity and accessibility to all the stakeholders to facilitate innovation. Also, H3a and H3c suggest that environmental factors like government regulations ($\beta = 0.281$, $p < 0.05$), and economic conditions ($\beta = 0.262$, $p < 0.05$) have a positive influence on AI/ML adoption. Compliance with industry specific regulations and guidelines is important for AI/ML adoption. Economic downturns impact market demands that can influence organization adoption of AI/ML. It was interesting to find that H1b perceived compatibility, H2a capability of organization and H3b localization failed to influence AI/ML adoption. These findings can be related to other technology factors like complexity and innovation overshadow the importance of compatibility. Organisational capabilities may be significant depending on the particular environment and industrial sector.

The findings indicate that internal policies and governance should be favorable for the organizations to decide on AI/ML adoption and complexity, and innovation aspects of technology are very relevant in adoption scenario.

Implications for theory

There are critical theoretical ramifications when utilizing the TOE framework to examine how automotive companies use machine learning (ML) and artificial intelligence (AI) techniques. TOE theory provides a holistic approach to adopting AI and ML in automotive organizations by considering organizational, environmental, and strategic aspects in addition to technological ones. An intensive investigation of the employees' skillsets, external forces and alignment of analytics to strategic decision support are all necessary for successful integration of AI and ML applications.

The use of TOE framework in the current study is appropriate to analyze the intricate interconnections from within and outside the realms of the organization. The study enables researchers and academicians to can gain knowledge of the causal mechanisms which drive AI and ML technology adaptation in the automotive sector. The study delved on the prospects and consequences of adopting AI and ML applications for insightful decision making. The study contributes to the framework by extending its validity and reach to an under-explored domain of data science adoption in the automotive industry.

Implications for practice

The study offers some critical implications to managers and practitioners in the automotive industry. It facilitates structure approach towards examine AI and ML applications in the automobile industry with practical insights. It also fosters a robust assessment of the endo and exogenous factors that impact insightful decision making enabled through AL & ML applications. Adoption obstacles can be carefully identified for planning and implementing resolution mechanisms for faster assimilation of AI and ML applications in critical processes from an end-to-end perspective.

The study also brought out the complications of implementing AI and ML applications in automobile companies by addressing the degree of customization, capability and compatibility issues. Even when they possess sophisticated capabilities, organizations may encounter difficulties because of organizational inertia, resistance to change, or inadequate strategy alignment. By considering these complex elements, TOE helps practitioners create all-encompassing adoption strategies. By identifying the complex interactions between technology, organizations, and environments, practitioners can more effectively overcome obstacles and increase the chances of successfully adopting AI and ML in automotive settings.

Conclusion

In conclusion, our study facilitates practitioners and managers in automotive organizations with a valuable lens for understanding and navigating the complexities of AI and ML adoption. The study endorses various components of technology, organization and environmental factors that impact the Al/ML adoption. While TOE illuminates critical factors influencing technology assimilation, the limitations of this study lie in its static framework and potential oversight of emerging dynamics. Future research should explore the evolving nature of AI and ML, considering dynamic contextual factors and adapting TOE to accommodate rapid technological advancements. By addressing these limitations and delving into the evolving landscape, researchers can offer more nuanced insights, aiding practitioners in orchestrating successful AI and ML integration strategies within the automotive sector.

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