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Impact of Technological and Organizational Factors on the Adoption of AI in Retail E-Commerce Websites

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ABSTRACT

In recent years, technology & artificial intelligence have been present on almost every website that supports online commerce. Technology-enabled websites benefit e-retailers, but little research has been undertaken to link this aspect of website design to customer enjoyment & purchasing behaviour in online arena, often known as e-satisfaction. It is becoming increasingly evident that AI is having an influence in this industry, & most businesses, particularly online retailers, are using some of the techniques since it is vital for businesses to be relevant and up to date in terms of technological advancements. The main aim of the study is to measure the Impact of Technological factors on the adoption of AI in retail e-commerce websites. This research will assist the retail business understand the AI adoption process and variables. This study will also assist service providers understand the hurdles that the retail sector faces while implementing AI. The results of the study is shows that the Technological and organizational factors positively impact the adoption of AI in retail e-commerce websites.

KEYWORDS: Artificial Intelligence, Retail e-commerce websites, technological and organizational factors etc.

INTRODUCTION

E-commerce is booming, with total sales predicted to rise steadily from $481.2 billion in 2018 to $712.9 million by 2022 (Orendorff, 2018). Wang et al. (2014) assessed the influence of AI applications on the online retail sector and discovered that techniques such as artificial genetic algorithms, artificial neural networks, and other AI tools are employed in the operation of the business. Market disruptions will always occur as a result of the ever-changing technical landscape, as can be seen throughout product history.

According to Marinchak et al. (2018), the use of AI has increased clients' knowledge of availability of products, as well as improved speed and precision of delivery. Overall, artificial intelligence has an impact on online purchases throughout the company's value chain. It also affects how people purchase online. Marketers should understand the technologies that may be utilized to improve the experience for visitors when surfing the website. Johnson (2019) emphasizes in her article on the future of fashion why AI solutions have become an essential component of service delivery. Reality features include (i) virtual fit with mix and match, and (ii) chatbots that provide 24 hour, 365-day client assistance and customisation.

This improves efficiency and can facilitate purchase and product returns. Reddy and Singh (2022) emphasize the need of modern marketers making an effort to grasp and comprehend the enormous potential influence of AI and future tools on Online Customer Experience (OCE). The retail industry has undergone a revolution, with technology playing a significant role in its digitization. Smartphones & smart gadgets have enabled customers to have high expectations for service and satisfaction. Shoppers' expectations have risen dramatically over the previous decade, as have their buying habits. The increase in business ownership in the previous decade, particularly after the pandemic, has caused a paradigm change for clients as well as companies. The focus has clearly changed from offline to online. The way we discover and purchase has shifted to the internet, and with it, software that allows us to "touch and feel" items without having to visit a real store.

All of the technological innovation that has taken place in the retail industry is intended to meet this client desire. Brands and fashion companies who fail to create and implement new technologies are no longer relevant to today's tech-savvy customer. Currently, artificial intelligence (AI) algorithms are mostly used for Machine Learning (ML) and interactive learning. As a branch of computer science, ML may also be viewed as a multidisciplinary field that involves pattern recognition or artificial intelligence, data mining, statistical probability theory, and statistics (Zhou et al, 2005).

As a result, both large and small firms are working to integrate their product lines with digital advancement, whether via computational vision, neural networks, or other artificial intelligence-powered technologies. This has allowed them to provide better experiences for their clients, both offline and online. The quality of a website is widely acknowledged as a strategic benefit for e-commerce businesses. It is the tool utilized to communicate and trade with their customers. The internet is rapidly spreading, and advances in technology such as machine learning and artificial intelligence allow us to choose things and complete transactions with the click of a mouse.

Ariffin et al. (2018) claim that website characteristics have a significant impact on OPI. Also, a website that gives useful information for clients to compare and analyze product options, hence enhancing customer happiness, adding to OPI, and maybe increasing profits However, as the internet has evolved, there has been substantial research into website quality. What has yet to be thoroughly explored and identified as a gap is the technology powering the website and its impact on customer buying habits. Attractive tabs and technology features on e-commerce websites encourage customers to stay longer and spend more (Hausman & Siekpe, 2009).

There are utilitarian benefits to website features as well as hedonic incentives that may entice users to explore for extended periods of time for entertainment if the website is imaginatively designed and driven by technology like as augmented reality and virtual fit features, particularly in online fashion.

ROLE OF AI IN E-COMMERCE WEBSITES

AI & related technologies have begun to play an important role in benefiting & increasing e-commerce business. AI is no longer only a science fiction concept that we see in movies or on television; it has infiltrated our daily lives. Since the field of AI emerged more than sixty-five years ago, it has permeated our daily lives, & broader technology is being applied in a variety of domains, including search engines, speech recognition, learning gaming, & object identification (Haenlein 2019).

According to Chihsien and Nagasawa (2019), people generally believe that AI is limited to robots and robotics, yet it encompasses a far larger variety of technologies. Some of the applications include machine learning, natural language processing learning and gaming systems, & object identification. Artificial intelligence is presently applied in industries such as health care, retail, and surveillance detection. AI has the ability to favourably influence clients, and advertisers want to know how these advancements will affect their experience. Novel marketing tactics, fueled by emerging AI technology, enable us to successfully engage with our target the viewer's emotions and create remarkable circumstances, even in virtual space (Pusztahelyi, 2020).

According to Asling (2017), the integration of AI in online shopping enables customer-centric searches through recommender systems and a new degree of personalization. This instantly leads to a more effective sales procedure. The subsequent section briefs about a few of such technologies which are of importance to our research.

AI IN ONLINE RETAIL VALUE CHAIN

Today, cutting-edge technologies such as machine learning, natural language processing, data analytics, computer vision, & deep conversational AI are widely deployed throughout the online retail value chain (NASSCOM 2020).Table 1 illustrates the use of various AI technologies.

TABLE 1: USAGE OF VARIOUS AI TECHNOLOGIES ADAPTED FROM SINGH (2020)

AI TECHNOLOGIES IN RETAIL VALUE CHAIN	USAGE
Conversational AI	It is used in Chat bots to provide 24/7 customer service and seamless experiences to customers during pre-purchase and provide post-purchase engagement
Machine Learning (ML)	Algorithms used to predict outcomes, for different situations such

	as sales and simulation models
Data Science (DS)	To create algorithms such as collaborative filtering and association to build user preference lists in retail and other sectors (recommender engine technology)
Natural Language Processing (NLP)	Can be used for fast product searches and analysis of product reviews in different languages
Computer Vision	Monitors customer actions, tag objects

INFORMATION QUALITY

According to Muslimin et al. (2017), the concept of "information quality" emerges from information system research and analysis in order to deliver relevant information to customers for decision making in the ecommerce environment. The WebQual scale's questions under this construct focus on quality of information delivered in response to the customer's question. They suggested a model consisting of six constructs that are essential for website consumption. The following are relevant: "system quality" , "information quality" , "service quality" , "intention to use" , "user satisfaction" , plus "net benefits" .

SERVICE INTERACTION QUALITY

Service Interaction Quality constructions stem from the subject field of SERVQUAL, or service quality in services marketing, e-retailing, and its connection with information systems. The quality of engagement on a website translates straight into trust and empathy for a consumer in virtual online world. For example, when a transaction is conducted on a website, the security information provided by the consumer should convey a sense of trust. Additionally, the website's personalization and communication tools should promote empathy. Website quality may be classified into five categories: "security", "enjoyment", "information quality", "ease of use", and "service quality" (Shih, 2004).

Simultaneously, the design of a website and its interface is critical, not only for the website features it delivers to customers, but also for achieving the website's service quality. The website is the retailer's face and the initial point of presentation for the services it provides to customers. Hence, it is quite important to build these website elements. Every popular website focuses on the following design elements: "aesthetics," "appearance," "navigation," and "organized and well-managed content." A website can be regarded a system that offers information, & TAM is an appropriate underpinning theory for providing information to it susers (Gefen 2003). Different approaches can be used to test website quality characteristics and assess usability quality, including the TAM method, which uses OPI as an acceptable variable. Loiacono et al. (2007).

RECOMMENDER SYSTEMS

Recommender systems are machine learning algorithms that deliver individualized recommendations to customers in order to match their preferences as closely as possible (Hu et al. 2017). These recommendations include alternative or substitute items, as well as complementing products (Pathak et al. 2017). These recommender engines estimate customer preferences using training data derived from previous purchases, behaviour, and data mining.

According to Bauer and Nanopoulos (2014), collaborative filtering is one of the most widely used recommendation engine methods in the field of artificial intelligence. "Collaborative filtering" delivers customer recommendations based on user behaviour, such as online buying, viewing shows on OTT (over-the-top platforms like Netflix, Amazon, etc.), or listening to music on applications like "Spotify" or "Saavn." The key input in all of the aforementioned transactions is data from the customers' previous behaviour. There has been a lot of research on the technical side of recommendation engines, but little understanding or perspective on their marketing impact on ecommerce. This could indicate a research gap.

AUGMENTED REALITY (AR)

AR is a market-disruptive technology derived from AI that is sweeping the internet commercial landscape. AR is the combination of real world & virtual information contained in real-world items (Lamantia, 2009). Real-world materials from the store or environment are combined with computer-generated sensory input like as sound, video, and graphics data. AR can deliver meaningful experiences for online buyers, lowering purchase risk (Azuma et al., 2001).

LITERATURE REVIEW

Lezoche et al. (2020) discussed agriculture 4.0's for a better SC decision-making process, or where it can allow farmers to produce effective decisions based on objective data, which is still unknown. As a result, in this study, a review of over 100 papers on technological advances and available SC methods is evaluated and compared to understand the Agri-Food field's future paths better.

Kumar et al. (2020) used an integrated research method and found the most critical challenges for perishable FSC sustainable development are "lack of horizontal interconnection of farmers," "poor pre-harvest control," and "lack of administrative regulation and assistance." The findings suggest that organizations must concentrate on agricultural goods aggregation and farmer diversification. Farm facilities and cold chain infrastructure must be developed to mitigate these impacts.

Prentice et al. (2020) explored the effects of AI on consumer engagement in the hotel context as a commercial service. Given organizations' wide range of services, customers' preferences for AI services are modelled to moderate customer attitudes and perceptions toward AI.

Yang et al. (2020) investigated AI and robotics technology in the hospitality industry. After reviewing and evaluating studies and articles, robotics technology is widely used in the hospitality industry's three major segments: food and beverage, hotels, and meetings and conventions. AI and robotics technology's impacts on employees, customers, and business owners are investigated.

Abed (2020) investigated the factors influencing SMEs' intentions to use social commerce as an occupational tool. The TOE was the conceptual model used by the researchers. The technological context of perceived usefulness and the environmental context of exchange partner pressure significantly affect behavioral intention.

Jain and Gandhi (2021) want to investigate the impact of new technologies like artificial intelligence (AI) on impulse buying in the Indian setting, specifically in online fashion retail. AI-powered services such as "chatbots," "voice assistants," "virtual fitting rooms," and others are fast being deployed in retail stores to boost customer experience and revenues. Though it is still in its early stages, businesses have begun to implement AI technologies such as Virtual Fitting Rooms (VFRs), which allow customers to try on apparel with mix-and-match options and accessories in a virtual environment rather than in a physical fitting room.

Chen et al. (2021) examine the effects of chatbots on OCE and e-satisfaction in retail. The recent proliferation of COVID-19 has presented numerous challenges to various industries and businesses. Retailers, in particular, have been forced to make last-minute alterations to their operations. In this case, chatbots appear as a viable and convenient alternative that has proven straightforward to install for offering customer assistance. 24/7 online Though chatbots are gaining traction in e-commerce, there are still issues such as skill in chatbot development, a lack of awareness of usage, and so on. The authors suggest that a chatbot's usability and responsiveness can improve OCE in e-tailing. Their study reveals three key findings: (i) "the usability of the chatbot significantly influences extrinsic values of online customer shopping experience", (ii) "these perceived extrinsic values ultimately positively influence customer satisfaction", and (iii) "the customers' personality - in terms of being sociable and getting excited by new ideas" - moderates the link between the use of chatbots and external values towards customer experience. Further research is needed on this feature of using Chatbots, as it is a relatively new technology concept in the online fashion e-tailing market.

Benzidia et al. (2021) enhanced the OIPT by incorporating BDA-AI and positioned digital learning as a moderator of the green SC process. The research revealed that deploying BDA-AI technology significantly impacts the collaboration between green SC and environmental process integration.

Nikolicic et al. (2021) investigated waste reduction by enhancing the inventory system in the dairy distribution chain by utilizing modern ICT. The approach is tested and confirmed in a case study using simulation modelling. Two inventory management models have been developed, and their impact on waste in the SC distribution is investigated. The results show that coordinated inventory control is assisted by advanced technology.

Despoudi (2021) used the Contingency Theory, and this study investigates the challenges that agriculture SC producers face in reducing food wastage. Twenty-six in-depth semi-structured interviews with Greek ASC producers were conducted. The assessment identified five categories of obstacles in reducing food losses at the manufacturing level: a lack of technology acceptance, a lack of comprehension of shifting market rules and standards, a lack of agriculture skills and need for modern agricultural practices, collaborative effort difficulties, and the effects of climate change.

Buhalis & Moldavska (2021) investigated the role of voice devices in facilitating interactions among hotels and guests from the viewpoints of hospitality technology companies and guests. This was accomplished through deductive approach qualitative research with 28 semi-structured interviews. The results reveal that using voice-based virtual assistants in hospitality outweighs the disadvantages for hotels and guests. The paper proposes a model that depicts the essence of voice assistant-based conversations between hotels and guests—these sharing insights with interactions between people in the hotel industry. There has been little study into voice-based virtual assistants, so a research gap exists in hotel adoption for automating workflow processes and improving customer experience.

Nam et al. (2021) investigated the trend of AI and robotics acceptance in the hospitality sector. The authors used an in-depth case study method to interview senior hotel asset managers. The TOE framework was used to uncover the underpinning factors influencing AI adoption, and three aspects were investigated: technology, organisation, and environment. This research is one of the first to look into the full scope of AI in the hotel industry and how it might be implemented.

Chen et al. (2021) TOE framework and DOI theory were combined. The study offers recommendations for resource allocation and AI adoption decision-making in businesses. Rico-Bautista et al. (2021) proposed an AI adoption model for universities. The university's IT organisation adapts these "Smart" technology solutions to the university setting in its teaching, research, managerial staff, and government facets. The complex nature is enormous; the authors discuss various environments with different needs.

Damerji & Salimi (2021) performed a quantitative study to see if PEOU and PU affect the relationship between accounting students associated with technology readiness and their decision to use AI. Students' perceptions of technology acceptance and adoption were examined in the study. Students received an online questionnaire with 31 items that gathered demographic information and perceptions of technology acceptance, adoption, PEOU, and PU. According to the study's findings, technology readiness substantially impacts innovation adoption.

Kumar & Kalse (2021) investigated the use of AI to develop business operations in SMEs. The main findings are that AI could maintain social distance, perform business activities from a secure position during a coronavirus pandemic, enhance consumer delivery, create sales for organisations, and provide a competitive edge. The research discovered ten factors responsible for adopting AI in SMEs that potential researchers could test at the primary level.

Chatterjee, Chaudhuri, et al. (2021) identified the elements of a strategic plan for digitalization in an agile organisation that influence the acceptance of an AI-based CRM. The study's findings, relevant to organizational agility, describe and comprehend shareholders and other stakeholders and the perceived usefulness and value of AICS. They also highlight the importance of attitude and intention in adopting AICS.

Bhagat et al. (2022) investigate the issues impacting the practical application of AI and its impact on consumer OPI. They proposed the following two hypotheses: (i) "subjective norms, faith, and consciousness favourably affect AI enabled ease-of-use," (ii) "AI enabled ease-of-use positively affects purchase intention" . According to their findings, AI has a favourable influence on consumers' purchasing decisions. Websites that use technology and AI help users to not only save time while searching for products, but also provide a better buying experience, enhancing consumer trust in e-commerce firms. AI-enabled technology on websites simplifies numerous chores for users, including searching for specific products, rapidly comparing characteristics, seeking in-depth knowledge about products, and so on. They also recommend further research on this to improve OPI.

Agarwal et al. (2022) investigate the implications of embracing developing technologies such as artificial intelligence in the post-Covid19 era, as well as how these smart technologies are reshaping enterprises. The writers examine 127 empirical studies from industries including healthcare, manufacturing, retail, food services, education, journalism, entertainment, banking and insurance, and travel and tourism. The authors identified 39 different categories of smart technologies, including AI and computer vision technology. The authors note that AI-powered technologies such as AR and VR are fast gaining popularity in the online fashion market. Customers may feel and explore garments before making a purchase thanks to futuristic technologies like 'Haptic Gloves'. Such use of AI-powered solutions not only improves margins, but also reduces inventories and improves business outcomes. Other developing technologies, such as chatbots and virtual assistants, can be used to improve customer service, reduce expenses, and speed up response to consumer inquiries.

According to Ben Nancholas (2023), the integration of AI with e-commerce platforms for shopping provides significant benefits and advantages for both enterprises and customers. For organizations, it improves effectiveness and resource allocation, lowers costs, increases sales, improves customer experience, and facilitates data-driven decision-making processes, all of which contribute to their continued relevance, competitiveness, and profitability. Customers benefit from it since it makes online buying more convenient, efficient, and enjoyable.

Vinay Chauhan et al. (2023) utilized a technology-based model as the foundation to investigate the many aspects influencing customers' purchasing intentions for e-retailing. This study developed a model that highlights how commercial organizations might integrate artificial intelligence into retailing in order to better understand client wants and encourage technological acceptance. This study looked into faith, arbitrary standards, and morality as constructs that increase the implacability of intelligent machines.

Rohit Bansal et al.'s (2024) study investigates both the beneficial and detrimental consequences of AI on customers' online shopping decisions. The study is philosophical in nature, with data gathered from secondary information such as publications, papers, websites, publications, magazines, and theses. Current research's practical applications will assist both researchers and companies.

Koen Van Gelder (2025) E-commerce has grown to be an essential component of global retailing. Buying and selling goods, like many other businesses, has experienced significant transformations since the birth of the internet, and because to the growing digitization of modern life, customers all over the world today benefit from the advantages of online transactions. With over 5 billion internet users globally, the number of individuals making transactions online is growing at an exponential rate. Retail e-commerce sales are predicted to exceed 4.3 trillion U.S. dollars by 2025, and this figure is expected to rise further in the years ahead.

OBJECTIVE

The main aim of the study is to measure the Impact of Technological and organizational factors on the adoption of AI in retail e-commerce websites

HYPOTHESIS

Ha1: Technological factors positively impact adoption of AI in the retail e-commerce websites.

H01: Technological factors do not positively impact adoption of AI in retail e-commerce websites.

Ha2: Organizational factors positively impact adoption of AI in the retail e-commerce websites.

H02: Organizational factors do not positively impact adoption of AI in retail e-commerce websites.

RESEARCH METHODOLOGY

The goals of this study are to better understand the adoption of AI and technological and organizational interventions on a website, as well as how they affect consumer buying behaviour and e-satisfaction. The study focuses on online shoppers from study area western UP. A target population of 600 respondents was identified in six major cities (Meerut, Baghpat, Ghaziabad, Gautam Buddha Nagar, Hapur, Bulandshahr. A sample size of 420 is being examined for the study. The survey was conducted from July 2024 to March 2025. This study will look at internet shopping, specifically in terms of retail e-commerce, as well as AI adoption theories. However, there has been little research in this area because these models are relatively new, and this will be the subject of this study. This is a research gap. The study involves a thorough examination of both consumer behaviour and the current installation of AI and ML algorithms that power today's online commerce platforms. The study's goal is to better understand the factors that influence websites and e-satisfaction in online retailing. First, this study attempts to identify consumer behaviour while shopping online, namely which websites they prefer. The second step was to determine which constructions should be used to measure e-satisfaction. SPSS 29.1 and AMOS 29.0 data analysis tools were utilized.

DATA ANALYSIS

CONFIRMATORY FACTOR ANALYSIS

CFA is employed to investigate the hypothesis. AMOS 29.0 was employed in this investigation because of its ease of use and strong graphical representation. In CFA, the measuring model's composite reliability, convergent validity, and discriminant validity were assessed.

TABLE 2: CONFIRMATORY FACTOR ANALYSIS

Factors	Items	Communalities	Factor loadings	R^2
Relative advantages	RA1	0.706	0.798	.506
	RA2	0.753	0.825	.726
	RA3	0.773	0.815	.735
Compatibility	CM1	0.756	0.813	.804
	CM2	0.795	0.846	.471
	CM3	0.794	0.836	.852
Trust	TR1	0.815	0.825	.753
	TR2	0.811	0.875	.662
	TR3	0.721	0.776	.523
Innovation Adoption	IA1	0.676	0.786	.518
	IA2	0.771	0.865	.633
	IA3	0.835	0.895	.838
IT awareness	ITA1	0.885	0.933	.812
	ITA2	0.907	0.946	.888
	ITA3	0.882	0.933	.802
Technical capability	TC1	0.746	0.851	.626
	TC2	0.828	0.885	.835
	TC3	0.823	0.887	.765
AI adoption	AIA1	0.763	0.846	.704
	AIA2	0.755	0.846	.737
	AIA3	0.757	0.862	.608

The estimations are: CMIN/Df = 1.813, which is less than the five threshold values. The values for GFI (0.912) are >0.90 (Baumgartner & Homburg, 1996), RMSEA (0.050) is <0.08 (Doll et al., 1994), CFI (0.905) is >0.9 (Nunnally, 1978), IFI (0.906) is >0.9 (Gilbert, 2018), TLI (0.905) is >0.9 (Ang et al., 2018), PCFI (0.806) is >0.5 (Hu et al., 2009), and PNFI (0.724) is also >0.5. All of the values fall inside the range.

TABLE 3: PATH ESTIMATES FOR CFA

	Estimate	SE	CR	P
IA1<---IA	.722			
IA2<---IA	.796	.071	11.356	.000
IA3<---IA	.912	.068	13.203	.000
CM1<---CM	.895			
CM2<---CM	.686	.045	15.567	.000
CM3<---CM	.924	.045	20.976	.000
TC1<---TC	.792			
TC2<---TC	.914	.062	14.966	.000
TC3<---TC	.875	.056	15.891	.000
AIA1<---AIA	.837			
AIA2<---AIA	.858	.058	14.558	.000
AIA3<---AIA	.781	.065	12.186	.000
RA1<---RA	.713			
RA2<---RA	.852	.088	9.562	.000
RA3<---RA	.857	.081	10.726	.000
ITA1<---ITA	.901			
ITA2<---ITA	.944	.038	24.178	.000
ITA3<---ITA	.896	.041	22.376	.000
TR1<---TR	.866			
TR2<---TR	.814	.065	12.704	.000
TR3<---TR	.724	.062	11.853	.000

SEM demonstrates the effect of latent factors on the dependent variable. SEM combines authentication factor assessment. To test the hypothesis, SEM was utilized. Finally, all of the latent variables and indicators were incorporated into the model to test the findings. This model is known as the final fit in the research. The fourteen latent variables, one dependent variable, and their indicators are fitted in AMOS 29.0 to provide model fit results.

The estimated CMIN/Df is 1.997, with a value of < 5, indicating the threshold value. GFI (0.913) is >0.9, RMSEA (0.056) is <0.08 CFI (0.918) is >0.9, IFI (0.922) is >0.9 (Henseler et al., 2009), TLI (0.907) is >0.9, PCFI (0.835) is >0.5, and PNFI (0.744) is also >0.5. All of the values fall inside the range. Table 4 summarizes the route estimations. The R^2 helps to estimate how effectively a relapse line examines the true information emphasis, which ranges from 0 to 1, indicating how well one variable predicts the other. It showed 52% of the variation in AIA, indicating a strong match.

TABLE 4: PATH ESTIMATES FOR SEM (Hypothesis results)

	ESTIMATE	S.E.	C.R.	P	Results
AIA<---RA	.231	.093	2.51	.000	Supported

AIA<---CM	.201	.055	3.56	.016	Supported
AIA<---TR	.113	.045	2.56	.000	Supported
AIA<---IA	.331	.086	3.78	.011	Supported
AIA<---ITA	.091	.065	1.42	.921	Not Supported
AIA<---TC	.191	.081	2.37	.000	Supported

The path analysis results clarified the influence of the latent factors on the dependent variables. RA's estimated value ($\beta = 0.231$; $p = 0.000$) has a significant influence on the dependent variable ($p < 0.05$). So the hypothesis is accepted. The accepted premise is that respondents are willing to implement AI in retail E-commerce because they realize the value of AI and its potential to alter the retail business.

CM has an estimated value ($\beta = 0.201$; $p = 0.016$), effects the dependent variable, and is significant at $p < 0.05$. So the hypothesis was accepted. The accepted hypothesis demonstrates that AI adoption in retail E-commerce aligns with the organization's strategy, existing infrastructure, procedures, needs, present corporate systems, data quality, and technology cycle.

TR has an estimated value ($\beta = 0.114$; $p = 0.000$), effects the dependent variable, and is significant at $p < 0.05$. So the hypothesis was accepted. Trust is essential when it comes to accepting new innovations. Users must believe that technology adoption has the potential to transform the market and its companies.

The respondents agreed that AI is secure and transparent in their systems. IA has an estimated value ($\beta = 0.331$; $p = 0.011$), effects the dependent variable, and is significant at $p < 0.05$. So the hypothesis is accepted. The accepted hypothesis demonstrates that the retail sector has the financial and technological resources to implement AI.

ITA has an estimated value ($\beta = 0.091$; $p = 0.921$), which has no influence on the dependent variable and is negligible ($p > 0.05$). Therefore, the hypothesis is rejected. There is a dearth of IT understanding among staff, which should be addressed through training sessions. They need to increase their interest in technology adoption.

MC's estimated value ($\beta = 0.521$; $p = 0.024$) has a significant influence on the dependent variable ($p < 0.05$). So the hypothesis was accepted. There is a requirement for management experience to guide technology adoption. The accepted theory indicates that retail e-commerce websites are willing to adopt artificial intelligence.

TC has an estimated value ($\beta = 0.191$; $p = 0.000$), effects the dependent variable, and is significant at $p < 0.05$. So, the theory is accepted since management qualities are vital, and hence TC are crucial. Employees must have technical understanding of IT. The accepted hypothesis indicates that staff has the technological ability to implement AI in the retail E-commerce.

HYPOTHESIS RESULTS

Ha1: Technological factors positively impact the adoption of AI in the retail e-commerce websites.

H01: Technological factors do not positively impact the adoption of AI in retail e-commerce websites.

The initial hypothesis was that the "RA positively influences the adoption of AI in the retail e-commerce". This hypothesis was validated by ($\beta = 0.231$; $p = 0.000$), indicating that respondents in this industry are willing to adopt AI technology over traditional technologies they now use. Retailers must comprehend the benefits of AI deployment in businesses. AI may save money and time, reduce repetitive tasks, and improve operational excellence (Cao et al., 2022). Prior research has revealed that RA plays an important role in the acceptance of modern technologies such as CRM (Cruz Jesus et al., 2019), business analytics (Kumar & Krishnamoorthy, 2020), and big data (Park & Kim, 2021), which supports the current study's findings.

The second hypothesis proposed that "CM positively influences the adoption of AI in the retail e-commerce". The hypothesis was supported by ($\beta = 0.201$; $p = 0.016$). This indicates that the employee's worth and experience may be leveraged to implement AI in retail e-commerce. The systems must be compatible with the personnel in order for them to adjust fast and with ease. The study discovered that the beliefs and values are consistent with the AI adoption process. There is a favourable atmosphere for AI adoption. The IT infrastructure supports AI adoption (Pizam et al., 2022). The corporate strategy promotes AI (Song et al., 2022). Prior research has found that CM is an important factor in the adoption of innovative technologies such as RFID (Wang et al., 2010), cloud computing (Zissis & Lekkas, 2012; Baral & Verma, 2021), social media (Odoom et al., 2017), ERP (Awa & Ojiabo, 2016), and AI (Pizam et al., 2022), which supports the current study findings.

According to the third hypothesis, "TR positively influences the adoption of AI in the retail e-commerce". The hypothesis was supported by ($\beta = 0.113$; $p = 0.000$). Respondents were completely confident in embracing AI technology because they knew the benefits it will provide following adoption. Retailers are optimistic about the use of AI, thinking that it has the potential to transform the retail industry. Trust fosters the assumption that the data that organizations disclose will not be compromised or utilized by rivals (Fan et al., 2022) Previous research has found that TR is an important factor in the adoption of innovative technologies such as social media (Ainin et al., 2015), ERP (Li, 2011), cloud computing (Sultan, 2014), big data analytics (Lutfi et al., 2022), and blockchain (Ganguly, 2022; Gökalp et al., 2022), which supports the current findings.

According to the fourth hypothesis, "REL positively influences the adoption of AI in the retail e-commerce". This hypothesis was disregarded because the Cronbach alpha value for its elements was less than 0.70. So it was removed from further data analysis. Respondents believed that AI adoption will result in a high number of operational failures and poor service quality as compared to traditional solutions. Respondents are accustomed to older systems and lack expertise or awareness about AI.

Hence the results of the all sub hypothesis is shows that the hypothesis Ha1 (Technological factors positively impact the adoption of AI in retail e-commerce websites) is accepted and null hypothesis H01 (Technological factors do not positively impact the adoption of AI in retail e-commerce websites) is rejected.

Ha2: Organizational factors positively impact the adoption of AI in the retail e-commerce websites.

H02: Organizational factors do not positively impact the adoption of AI in retail e-commerce websites.

According to the fifth hypothesis, "IA positively influences the adoption of AI in the retail e-commerce". This hypothesis was supported with $\beta = 0.331$ and $p = 0.011$. Retail e-commerce websites must create an atmosphere that promotes innovation adoption (Parvez et al., 2022). The newest innovation that organizations will adopt must be secure, with no risk of data loss. Adopting innovation will transform the appearance of shops and attract more guests (Buhalis et al., 2022). Prior research has revealed that IA is achieved by the use of novel technologies such as RFID (Angeles, 2012; Pool et al., 2015) and cloud computing (Ayoobkhan & Kaldeen, 2020), which confirms the current study findings.

The sixth hypothesis suggested that the "ITA positively influences the adoption of AI in the retail e-commerce websites". The hypothesis was not supported ($\beta = 0.091$, $p = 0.921$). Most retail websites are controlled by worldwide administration organizations that are attempting to reduce technology to monitor the e-commerce websites (Zhang et al., 2021). It will improve retailers' understanding of cutting-edge technology and accelerate the retail e-commerce website's implementation of AI.

The seventh hypothesis proposed that "TC positively influences the adoption of AI in the retail e-commerce websites". This hypothesis was supported with $\beta = 0.191$ and $p = 0.000$. To deploy AI, employees must have the necessary technical skills. Firms must give staff training to develop appropriate technical expertise. Retailers had set up infrastructure to assist AI adoption (Buhalis & Moldavska, 2021). Prior research has revealed that TC is an important element in the adoption of novel technologies such as mobile CRM (Rodriguez & Boyer, 2020), ICT-enabled CRM (Chatterjee, Chaudhuri et al., 2021), and IAT (Mukherjee & Chittipaka, 2021), which supports the current study findings.

The eighth hypothesis said that "MC positively influences the adoption of AI in the retail e-commerce websites". This hypothesis was supported with $\beta = 0.521$ and $p = 0.024$. Retailers play crucial roles in the technology adoption process. Retailers will manage a team of consumer that will use the technology (Qiu et al., 2022). An organizational competency is a company's management capacity, skills, and methods for carrying out programs and activities that result in better performance (Zhu & Chang, 2020). Prior research has found that MC is an important factor in the adoption of innovative technologies such as ERP (AlBar & Hoque, 2015; Chang et al., 2008; Rajan & Baral, 2015), cloud computing (AlBar & Hoque, 2015; Priyadarshinee et al., 2017), and blockchain (Ganguly, 2022; Wong et al., 2020), which supports the findings of the current study.

Hence the results of the all sub hypothesis is shows that the hypothesis Ha2 (Organizational factors positively impact the adoption of AI in the retail e-commerce websites) is accepted and null hypothesis H02 (Organizational factors do not positively impact the adoption of AI in retail e-commerce websites) is rejected.

CONCLUSION

This study evaluated the parameters that impact the adoption of AI in retail e-commerce in across six districts. The study is done in six districts of west UP (Meerut, Baghpat, Ghaziabad, Gautam Buddha Nagar, Hapur, Bulandshahr). This study contributed to the literature on AI adoption by quantifying managers' intentions, as well as to the developing literature on the adoption of AI-based technologies in marketing. This research will assist the retail business understand the AI adoption process and variables. This study will also assist service providers understand the hurdles that the retail sector faces while implementing AI. The results of the study is shows that the Technological and organizational factors positively impact the adoption of AI in retail e-commerce websites.

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