Transformative Role of Artificial Intelligence in the Hotel Industry of Jammu, Kashmir, and Ladakh Post Article 370: Opportunities and Challenges

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ABSTRACT

This paper analyses the adoption of Artificial Intelligence (AI) in the hotel sector of Jammu, Kashmir, and Ladakh (JKL) using a synthesis of theoretical perspectives on the subject by combining the Technology Acceptance Model (TAM) and the Diffusion of Innovation (DOI) theory. Whereas AI-driven change in the hospitality sector has been a widely researched topic in urban and technologically developed markets, little has been done to examine adoption dynamics in geographically marginalized and infrastructure-sensitive tourism economies. The study uses qualitative secondary data research design in which it systematically synthesizes peer-reviewed literature, government reports, regional tourism statistics and policy documents. The results show that perceptions of usefulness expressed in terms of revenue optimization, efficiency, personalization, and predictive maintenance is a major influence on adoption intention. Such attributes of diffusion as relative advantage and observability that are owed to DOI promote diffusion further, especially in competitive tourism settings. Adoption is however regulated by structural factors such as infrastructural differences, SME dominance, skill limitations in the workforce and seasonality effects in tourism which increase perceived complexity and financial risk. The research extends the adoption theories of innovation by adding structural moderators to the TAM-DOI model and offers region-specific findings on digital transformation in the peripheral hospitality systems. The results can help AI-hospitality literature by providing a context-based theory-based account of the technological diffusion in developing tourist destinations.

Keywords: Artificial Intelligence, Hospitality Industry, Technology Adoption, Innovation Diffusion

INTRODUCTION

Global Digital Transformation in Hospitality

There is a global digital transformation in the hospitality industry as outlined in 1.1. The world hospitality sector is experiencing a radical digital revolution as a result of the blistering changes in Artificial Intelligence (AI), machine learning, data analysis, and the Internet of Things (IoT). The use of AI has transformed into both a support tool and a strategic enabler that alters operational frameworks, services delivery, and competitive positioning of the tourism ecosystem (Buhalis & Leung, 2018). Hotels are increasingly using AI-based chatbots, robotized check-in systems, service assistants, predictive analytics, and smart room technologies to embrace a more efficient and personalized business approach (Tussyadiah, 2020). AI uses a system of strategic transformation because it redirects operations within the hospitality industry to an approach that is reactive in terms of service delivery, predictive, and data-oriented management. Machine learning algorithms can help the hotel predict demand, optimize dynamic pricing, and improve revenue management systems (S. Ivanov & Webster, 2024).Operational automation reduces human error, accelerates service processes, and lowers administrative costs, thereby strengthening profitability in highly competitive markets (Huang & Rust, 2022) Meanwhile, personalization capabilities allow hotels to customize recommendations, amenities and marketing communications based on their guest preferences, which improves consumer satisfaction and loyalty (Morosan & Dursun-Cengizci, 2024). Competitiveness based on the use of technology has consequently become a characteristic in the modern hospitality markets. Digital capability ceases to be an option and a part of resilience and long-term strategic positioning (Sigala, 2018). Contactless service, digital interfaces, and automation have come to the fore, especially following the COVID-19 pandemic, and are enhancing the use of AI in global hotel chains (Tussyadiah, 2020). Nevertheless, although multinational and urban hotel networks follow the trend of fast technological integration, the patterns of adoption are not even in all geographical and economic settings.

Emerging and Peripheral Tourism Economies: AI Adoption.

AI Adoption in Emerging and Peripheral Tourism Economies

Nevertheless, AI technologies are spread all over the world, and their application in the emerging and peripheral tourism economies is unequal. The presence of structural discrepancies in digital infrastructure, monetary capacity, and workforce abilities establishes a consistent digital gap between metropolitan hospitality locales and geographically distant destinations (Buhalis & Amaranggana, 2015). Advanced AI systems require the highspeed internet connectivity, dependable electrical supply, and cloud data platforms, and cybersecurity systems, which are not distributed uniformly across tourism regions. The perceived feasibility and ease of use of AI technologies are extremely dependent on infrastructure constraints. In a lot of developing or mountainous locations, the unreliable broadband connection and poor technology ecosystem can limit the implementation of real-time data analytics and automated management systems (Gajić et al., 2024). The adoption is also deterred due to financial constraints, especially with small and medium-sized enterprises (SMEs) that take over the peripheral hospitality markets. Experimentation with advanced technologies is usually deterred by high initial investment costs, uncertainty around the return on investment (ROI), and seasonal variation of demand (S. H. Ivanov et al., 2017). Another important determinant is the capability of the workforce. The implementation of AI needs digital literacy, technical education, and organizational culture adjustment. Nevertheless, new economies often experience skills shortages, which drag down the adoption of technology (Murphy et al., 2019). Another reason that could cause resistance to automation is the fear of job replacement or cultural inclination to human-centered service provision. Notably, all of the available academic literature is mostly focused on urban hotels, international chains, and high-tech markets (Tussyadiah, 2020). There is a paucity of studies on the dynamics of AI adoption in mountainous, seasonal, and infrastructure-constrained tourist economies. Peripheral regions tend to have unique features including environmental vulnerability, seasonal patterns of tourism, and dependence on small family-owned businesses which can influence the process of innovation diffusion differently than in metropolitan areas. Thus, the analysis of the use of AI in such areas is a valuable source of information regarding the mediation of technological change by structural and institutional factors.

Regional Context: Jammu, Kashmir, and Ladakh

Jammu, Kashmir and Ladakh (JKL), is a region with geographical diversity and relies on tourism as a traditional economic activity with natural scenery, pilgrimage activities, adventure tourism and cultural heritage as the main tourist attraction sites. Tourism is one of the most important sectors of the economy that plays the role of employment creation, diversification of regional income and development of small enterprises (Ministry of tourism, 2023). Hotel business is a basic part of this tourism ecosystem that sustains accommodation facilities in cities, pilgrimage and wild mountain regions. The focus on the infrastructure development, the promotion of the tourism industry, and the inflows of private investments have renewed the attention to the region since 2019. The development of connectivity, road systems and destination marketing campaigns have also led to a rise in domestic tourist arrivals in various districts (Ministry of tourism, 2023). Although the development of tourism has made service modernization a possibility, it has also added a significant level of competition to the hotel industry, making the service quality and efficiency of operations hard to be improved (Buhalis & Amaranggana, 2015). Nevertheless, there are a number of structural constraints of the regional hospitality structure. To begin with, tourism within JKL is very seasonal with the peak demand being demanded during certain months owing to climatic conditions. Seasonal changes cause the

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unpredictability of revenue and affect long-term technological upgrade investment choices (Baum & Lundtorp, 2001; BUTLER, 1980). Second, the topography and scattered habitation is an infrastructure issue such as poor internet coverage and logistical impediments. The effect of digital infrastructure differences on technological adoption is found to be quite pronounced in peripheral tourism destinations (Buhalis & Leung, 2018). Third, hospitality business in the region is mostly a small and medium sized enterprise (SMEs) as opposed to multinational chains. SMEs usually have small capital bases, capacity of managers, and technological knowhow that may influence the innovation trial and willingness to adopt (S. H. Ivanov et al., 2017). These structural factors render JKL an analytically important case to study the adoption of AI in a periphery and infrastructure-vulcanized tourism economy. Although AI technologies also have the potential to enhance revenue optimization, customer personalization, and operational management, their viability and penetration depend on contextual economic, institutional and infrastructural realities (Davis, 1989).

Research Gap

Despite being the focus of modern hospitality studies, AI is still underlined in the majority of the available literature, as it focuses on big global chains of hotels, smart cities, and high-tech markets (Tussyadiah, 2020). Automation tools, robotics, and predictive analytics are often identified as the most important tool in process of automation development through empirical study that overlooked the way in which regional structural conditions mediate the adoption process. Additionally, numerous researches have followed descriptive methods which define how technologies are used as opposed to basing the analysis on existing innovation theory. Theoretical models (e.g., Technology Acceptance Model (Davis, 1989) or Diffusion of Innovation Theory (Rogers, 2003) in examining AI adoption within region-specific hospitality contexts. Research focusing on peripheral destinations particularly mountainous and seasonally volatile tourism economies remains scarce. The interplay between infrastructural readiness, SME dominance, cultural service norms, and technological innovation has not been sufficiently explored in the context of AI-driven hospitality transformation.

Gap Statement: Although there is an increase in scholarly research in AI in hospitality, few studies are systematic in the examination of technology adoption dynamics in low-density and geographically marginal tourism economies that are limited by infrastructure research through established innovation theories. To fill this gap, the current research uses a theoretical approach to examine AI adoption motivation and obstacles in the hotel sector of Jammu, Kashmir, and Ladakh, thus making a contribution to the local tourism literature and the overall technology adoption literature in the hotel sector.

Research Objectives

1. To determine the drivers of AI adoption in the hotel industry of JKL through TAM and DOI.
2. To determine the structural and organizational obstacles which affect diffusion.
3. To determine the impacts of AI adoption on the competitiveness of regional tourism.

LITERATURE REVIEW

AI in Global Hospitality: From Automation to Augmentation

Artificial intelligence (AI) has become a disruptive technology in the hospitality industry worldwide, transforming the system of operations, service delivery model and approaches to customer engagement. The initial uses of AI in hospitality were more on automation and efficiency improvement (chatbots to interact with customers, automated concierge services, automated check-in kiosks, and algorithmic revenue management systems) (S. H. Ivanov et al., 2017). These technologies were first implemented to cut labor dependence, decrease normal cost of operation and improve standardization of processes. The use of robotics and service automation has especially been prevalent with the large international hotel chains. The robots can also be used in housekeeping assistance, room service delivery, and front-desk assistance, which help to make the service delivery faster and more precise (Huang & Rust, 2022). The AI-based chatbots and virtual assistants allow 24/7 customer support, multilingualism, and real-time control of the booking process, which enhances the efficiency of response and the workload of the front office (Tussyadiah, 2020). Predictive analytics-based revenue management systems also facilitate dynamic pricing procedures that rely on demand forecasting, competitor, and occupancy trends (S. H. Ivanov et al., 2017). Nevertheless, modern research is starting to indicate how AI has found its way in hospitality to no longer be focused on cost-cutting to value co-creation and service enhancement. Instead of completely substituting human interactions in the context of service, the introduction of AI technologies is being offered to enrich them with a human interaction, allowing to differentiate it even more personally and experience-based (Morosan & Dursun-Cengizci, 2024). An example is that machine learning algorithms can be used to examine the preferences of the guests and their past booking behavior to create personalized recommendations, personalized experiences, and personalized marketing communications. This augmentation as opposed to automation is a response to a more general change in the strategy of hospitality, the shift between operational efficiency and experience-focused competitiveness (Sigala, 2018). The controversy of the cooperation of the human and AI has become popular over the past few years. Researchers claim that hospitality as the industry, which heavily depends on services, is highly dependent on the qualities of emotional intelligence, empathy, and cultural sensitivity that cannot be easily implemented by the AI systems (Murphy et al., 2019). Although automation is efficient, overdependence on AI can also threaten to eliminate the human touch on which the traditional hospitality experience is built. Huang & Rust (2022) suggest a joint intelligence model, with AI running analysis and repetitive services, and human employees being concerned with interrelationship and emotional complex relations. According to this hybrid model, the adoption of technology should be based on the strategy of integrating values of services instead of a cost-cutting tool. Although AI applications are expanding very fast, the results of the empirical research are controversial. In some studies, there are positive effects related to customer satisfaction and operational productivity (S. Ivanov & Webster, 2024). whereas in others, there are issues related to trust, privacy, and acceptance of AI-mediated services by the guests (Morosan & Dursun-Cengizci, 2024). Such different results show that the adoption of AI is context-dependent and relies on the organizational, cultural, and infrastructural factors. This means that the phenomenon of adoption cannot be studied without leaving the description of technologies to a more organized theoretical analysis.

Technology Adoption in Hospitality: Determinants and Barriers

Implementation of new technology in hospitality is determined by various organizational and environmental factors. One of the most important causes and limitations is financial capacity. The implementation of AI may involve high initial costs in equipment, software integration, and cybersecurity solutions, as well as training of employees. These costs are more likely to be absorbed by big hotel chains that have diversified their levels of revenue than by small and medium-sized businesses (SMEs) (S. H. Ivanov et al., 2017). Research shows that the perceived return on investment (ROI) is an important factor that can determine the willingness of managers to embrace automation technologies (S. Ivanov & Webster, 2024). The uncertainty surrounding the financial returns in a scenario where there is volatility in demand or the seasonal tourism may delay the adoption decision. Another important determinant is skill preparation. The digital literacy, technical skills, and organizational capability is required in the integration of AI. Hospitality employees will have to get used to AI-enabled workflow, data analytics, and automated decision-support solutions (Murphy et al., 2019). Lack of proper training infrastructure and lack of exposure to digital systems, may generate a change resistance that minimizes technology acceptance in the staff. John T. Bowen Cristian Morosan (2018) stress that the adaptability of the workforce is one of the key mediators of a successful AI implementation in the service sectors. Culture in organizations is also very crucial. Innovation leadership and technology positive outlook of hotels have more chances to experiment with AI solutions. In the opposite scenario, the traditional management organization with the emphasis on manual work processes might find the impact of automation to disrupt the established service ideas or erode the perceived service authenticity, or even lose the control of the automated decision-making processes (Sigala, 2020) Adoption feasibility is also further influenced by infrastructure dependency. The functioning of AI systems is based on the absence of unstable internet connections, the presence of a cloud computing environment, and integrated property management systems (Buhalis & Leung, 2018). Poor digital facilities may raise the complexity of implementation and the perception of ease of use. This issue is especially apparent in remote or developing tourist destinations, where broadband penetration and technological ecosystems might be skewed. Notably, a significant portion of the current studies on the phenomenon of technology adoption in the hospitality industry are based on the research carried out in the urban and technologically advanced settings. Research is often conducted on the adoption behavior in urban hotels, chain hotels, and smart cities (Tussyadiah, 2020). Although these results are good insights, their transferability to marginal or infrastructure-starved areas has not been well studied. Besides, theoretical underpinning in studies on hospitality technology differs significantly. Even though models like the Technology Acceptance Model (Davis, 1989) and Diffusion of Innovation Theory (Rogers, 2003) are commonly utilized in the fields of information systems, their methodical integration into the regional hospitality AI research is sparse. Numerous empirical studies explain the technological applications without thoroughly analyzing cognitive, organizational, and structural factors that affect the adoption decisions.

AI in Emerging Economies and Peripheral Regions

The implementation of AI in developing economies and in geographically marginalized areas is a peculiar challenge and dynamics. Lack of digital preparedness has been a primary concern. The areas of development are prone to inequalities in the availability of the internet, investments in digital infrastructure, and technological literacy (Adebayo Olusegun Aderibigbe et al., 2023). Such differences are contributing factors to a digital divide that influences the competitiveness in tourism and modernization in the service. Technology diffusion is even further complicated by institutional constraints. The legal systems of data protection, cybersecurity, and digital innovation might be underdeveloped or applied inconsistently in new situations. Unstable institutional backing may deter the use of AI systems privately because of the uncertainty there about regulation (Buhalis & Amaranggana, 2015). Besides, a lack of opportunities to pilot implements or develop experimentally may be caused by the limited public-private partnerships and the lack of government incentives. Another structural constraint is SME vulnerability. The smaller hotels and independent operators of the peripheral tourism economies are often dominated by small family hotels. The SMEs may not have economies of scale, diversified sources of capital, or technological alliances needed to conduct AI experiments unlike multinational chains (S. H. Ivanov et al., 2017). Financial risk is further increased by seasonal demand trends which are prevalent in mountainous or pilgrimage destinations and make long-term digital investments less predictable. Studies also indicate that peripheral areas have a cultural context that determines the acceptance of technology. In the place where there is a high culture of personalized and relational hospitality, automation could be seen as impersonal or culturally incompatible (Murphy et al., 2019). Tourists in the heritage or nature-based sites might want to focus on more real human interaction rather than a technological mediated service delivery. Therefore, the implementation of AI in this context might need some hybrid solutions that would combine automation with service practices that are inherent to the culture. Although these unique attributes indicate that empirical studies that specifically investigate the use of AI in mountainous, seasonally volatile or infrastructure-sensitive tourism areas are few. The available literature is mostly based on national-level strategies of digital tourism or covers the case studies of metropolitan regions. Micro-level studies of the bargaining of structural limitations by peripheral areas of hospitality in the attempt to modernize technologically are inadequate (Sánchez et al., 2025).

Critical Synthesis and Identified Gap

A critical review of the literature indicates that there are a number of conceptual and empirical weaknesses. First, the AI research in the hospitality industry is mostly urban-based and chain-oriented. The majority of the empirical studies examine the adoption of technology in technologically developed markets without considering the geographically isolated destinations, which have weak infrastructures. This brings about a contextual bias which constrains generalization. Second, it is not empirically supported by mountain and seasonal tourism economies. Areas that are vulnerable to the environment, have logistical issues, and SME presence might have varying adoption patterns than metropolitan hospitality centres. However, all these contexts are still underrepresented in AI-hospitality scholarship mainstream (Sánchez et al., 2025). Third, there is uneven theoretical application in the regional hospitality technology research. Although the basic innovation theories like the Technology Acceptance Model (Davis, 1989) and Diffusion of Innovation Theory (Rogers, 2003) provide systematic frameworks to study the behavior of adopting innovation, their application in the research of the peripheral tourism economy is still poor. A majority of the studies follow descriptive methods where AI tools are catalogue listed instead of studying perceived usefulness, complexity, compatibility, or diffusion attributes in a systematic manner. Lastly, structural modulators like infrastructure preparedness, institutional assistance, workforce potential, and seasonality and innovation distribution are not well theorized. The absence of the frame of adoption makes the process of technological change in situational hospitality ecosystems complicated to comprehend. Hence, it is evident that a theory-based, locally-based study that focuses on analyzing AI adoption trends in less developed tourism economies that are peripheral and constrained by infrastructures is necessary. An organized framework that combines technology acceptance and innovation diffusion viewpoints can present more insight into how the integration of organizational perceptions, structural conditions, and environmental factors influence the AI implementation in a hospitality setting.

THEORETICAL FRAMEWORK

The adoption of Artificial Intelligence (AI) in the hospitality industry needs a systematic analytical tool that can elucidate organizational decision-making and diffusion processes in the system. Although previous research often outlines the use of technology in hotels, there are only more instances wherein the use of established theories of innovation is considered to explain how the adoption behavior is applied in the contextual setting. The current study, therefore, to fill this gap relies on two matching theoretical perspectives including the Technology Acceptance Model (TAM) (Davis, 1989) and Diffusion of Innovation Theory (DOI) (Rogers, 2003). TAM posits the influence of perceptions on the technology acceptance at the personal/managerial level, and DOI takes a more general organizational/systemic view of the distribution of innovations in social systems. Combined, these frameworks provide a multi-level analysis framework of the AI adoption in hospitality, especially in tourism economies which are geographically peripheral and sensitive to infrastructures.

Technology Acceptance Model (TAM)

One of the most used models used to explain the user acceptance of information system is the Technology Acceptance Model (TAM) first introduced by Davis (1989) TAM assumes that two cognitive determinants, including perceived usefulness and perceived ease of use have the major impact on the adoption of technology. It is these perceptions that lead to behavioural intention, which in turn predicts actual system use.

Perceived Usefulness

Perceived usefulness is the levels at which one believes that the employing of a certain technology will result in job performance improvement (Davis, 1989). The concept of perceived usefulness in the hospitality industry is conveyed into managerial determinations of whether AI technologies can enhance operational effectiveness, generate revenue, customer satisfaction, or competitive advantage. Computer-assisted technologies like predictive analytics, revenue management systems, chatbots, and smart room systems are normally measured using quantifiable performance results. Researchers find that hotels that implement AI in their operations and use it in dynamic rates and demand services have a better occupancy rate and profitability due to better services customized to the needs of each consumer (S. Ivanov & Webster, 2024). and that AI-powered personalization systems are better at customer engagement and retention with their services being tailored to consumer needs (Morosan & Dursun-Cengizci, 2024). Perceived usefulness has a close relation to return on investment (ROI) in the case of hotel managers. The adoption decisions in capital sensitive environments are made under the condition of explicit performance benefits. In cases where AI systems prove to be cost-effective, more energy efficient, or increase revenue, willingness to adopt these systems on the part of the managers goes up (S. H. Ivanov et al., 2017). On the other hand, unclear financial benefits can decrease the perceived usefulness and slow down implementation. Perceived usefulness is even more important in a peripheral tourism economic system where demand is seasonal. Managers need to answer the question of how AI can be used to cut the volatility, to streamline their operations in peak seasons, and to optimize their resources in off-peak seasons. Thus, the usefulness perception plays the role of strategic filter determining adoption decision at the organizational level.

Perceived Ease of Use

Perceived ease of use is how one feels that there will be no effort in using a system (Davis, 1989). When applied in a hospitality environment, this construct is associated with the technical sophistication of AI implementation, the compatibility of the system with the current property management software, and the presence of highly qualified people who will be able to use sophisticated technologies. The AI systems can be viewed as technically challenging by hotels that are operating in an infrastructure-constrained environment. The perceived difficulty can be enhanced by limited broadband connectivity, insufficient IT assistance, and problems with integration, which in turn will decrease the level of acceptance (Buhalis & Leung, 2018). Also, the perceived ease of use depends on the digital literacy of employees. Resistance to change can be developed when employees have no knowledge of automated systems or data analytics platforms (Murphy et al., 2019). The concept of skill-based resistance is especially applicable in localities that have a high concentration of small and medium-sized enterprises (SMEs). SMEs usually have a scarcity of managerial experience compared

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to multinational chains, which have their own IT department. When AI technologies are viewed as difficult or threatening the normal working processes, the perceived ease of use decreases, which adversely affects the behavioural intention.

Behavioural Intention

Behavioural intention is the motivational dimension, which defines how managers or organizations can be interested in adopting and implementing AI technologies In the hospitality industry, behavioural intention is reflected in strategic investment choices, pilot program execution and long-term planning of digital transformation. The perceived usefulness and perceived ease of use intersect to form behavioural intention. Indicatively, despite the high-performance benefits that AI systems may have, there may be no adoption in the event that integration is seen as too complicated. On the other hand, user-friendly technologies with limited strategic value cannot produce long-term interest. Empirical studies within hospitality support the fact that managerial perceptions do play a critical role in automation decisions (S. Ivanov & Webster, 2024) TAM therefore explains AI adoption at the cognitive level as a form of linking perception-based judgments to strategic behaviour. Nevertheless, TAM deals mostly with the individual or organizational decision-making. It fails to comprehensively describe the process of innovations spreading between territories or the influence of structural factors on diffusion. Due to this reason, Diffusion of Innovation Theory is a complement to TAM since it offers an overall perspective.

Diffusion of Innovation Theory (DOI)

The spread of innovations in social systems over time can be explained by Diffusion of Innovation Theory (Rogers, 2003) DOI suggests that there are five attributes of innovation that determine adoption, relative advantage, compatibility, complexity, and trialability, observability. The attributes will determine the diffusion speed and scope of organizations and regions.

Relative Advantage

Relative advantage is deemed as the perceived excellence of an innovation in the view of the current practices (Rogers, 2003) The AI technologies should show observable positive changes in hospitality in relation to traditional models of service. Such enhancements can be better operational efficiency, more customization of guests, lower labor expenses, or greater revenue maximization. Perceived relative advantage is high when hotels notice that the competitor that uses AI to provide a high level of occupancy or higher levels of guest satisfaction. Evidence-based monetary and experience advantages facilitate uptake due to competition (S. H. Ivanov et al., 2017). Contextual constraints should also be considered in relative advantage in the case of the peripheral tourism economies. In the areas where the logistical or environmental factors are problematic, AI systems that optimize energy consumption or automatize the resources management can be of more value.

Compatibility

The level of compatibility is a term that describes the extent in which an innovation is congruent with prevailing values, practises, and culture of an organization (Rogers, 2003). The hospitality sectors that are based on the tradition of personalized service might view the automation of AI as culturally incompatible when it comes to diminishing the aspect of human interaction. Studies demonstrate that there are still controversies over the issue of the balance of efficiency and emotional service provision through technology (Huang & Rust, 2022). In culturally oriented and relationally oriented destinations, the use of AI should not substitute the human interaction but support it. The compatibility goes also to technological infrastructure. Artificial intelligence systems should be incorporated in the current property management systems and reservation systems. Misalignment creates more obstacles to implementation and slows down the rate of diffusion.

Complexity

Complexity is a factor that indicates how difficult it is to comprehend and apply an innovation (Rogers, 2003). Diffusion is slowed by high complexity. Geographically fragmented or mountainous areas can make infrastructure constraints perceived complexity because of unstable connection and poor technical support. Complexity is acting with the construct of perceived ease of use of TAM. The combination of these dimensions describes the role of technical barriers in adoption hesitation.

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Trialability

Trialability is the degree to which an innovation can undergo a limited trial before being used in a full-scale way (Rogers, 2003). The model to test AI chatbots or revenue management tools on pilots enables the hotels to test the results of performance without investment of significant capital. Trialability minimizes financial risk in seasonal tourism markets because it allows an adoption phase. Reduced experimentation boosts confidence by the managers and reduces uncertainty.

Observability

Observability is the subject of how the innovation results are seen by other people in the social system (Rogers, 2003). Imitation effects facilitate diffusion when successful AI use is noticeable in other comparable hotels or other rival destinations. Smart tourism demonstration projects, Government-funded, and publicized case-studies make the industry more observable, and impact patterns of industry wide adoption.

RESEARCH METHODOLOGY

The proposed project follows a qualitative secondary research design based on an interpretive inquiry that is theory-based to investigate the adoption of Artificial Intelligence (AI) in the hotel sector of Jammu, Kashmir, and Ladakh (JKL). An appropriate research methodology should be a secondary one in those situations when technological change is dynamic and proprietary data of firms is still restricted (Johnston, 2014). In the studies on hospitality and tourism, the analysis of secondary data has been prevalent to generalize the digital transformation trends, the diffusion patterns of innovation, and the trends of modernization of the region. Instead of providing an overview of AI applications descriptively, this paper analytically interprets the available empirical evidence in terms of analytical perspectives of the Technology Acceptance Model (TAM) and Diffusion of Innovation (DOI) theory. Placing the research in a conceptual framework makes the concept conceptually sound and analytically rigorous. The study design is interpretive oriented as it acknowledges the fact AI implementation in hospitality is a socio-economic, infrastructural and organizational phenomenon. TAM offers a micro-level explanatory model concentrating on the usefulness perceptions, ease of use perceptions, and behavioural intention whereas DOI proposes a macro-level diffusion model that takes into account relative advantage, compatibility, complexity, trialability, and observability. By combining the theoretical frameworks chosen, it will be possible to adopt a multi-level analytical approach in which the managerial perceptions will be integrated with the more general structural determinants. The theoretical approach to the strategy enables the analysis to go beyond descriptive classification and to an organized description of dynamics of AI adoption. The systematic review and triangulation of various secondary sources were used to collect data, therefore, demonstrating evidentiary robustness. The main database was composed of peer-reviewed academic literature, which was accessed via the well-known academic sources with such keywords as Artificial Intelligence in hospitality, AI adoption in tourism, and technology acceptance in hotels. The focus was made on quality hospitality and tourism journals in order to guarantee academic dependability. These references were used to find empirical information on the topic of automation, revenue maximization, guest personalization, and managerial technology acceptance. Official tourism reports, policy documents, and regional tourism statistics were examined as a way of contextualizing the regional dynamics in order to measure the patterns of tourism growth, the creation of infrastructure and the digital transformation efforts. Minimal use of industry white papers and consultancy reports was done to identify macro-level global AI trends; these materials were both cross validated with academic research to remain scholarly. The interdisciplinary approach of academic, policy, and statistical data increased the quality of the results and reduced the bias of one source. The analytical process was based on a four-stage process. To begin with, systematic literature screening was done based on the preset inclusion criteria, such as peer-reviewed status, recent publication date, and direct relevance to AI adoption or innovation in hospitality. Research that concentrated on the technical engineering elements and not on the application in the hospitality industry was eliminated. Such a screening procedure increased the methodological transparency and minimized the selection bias. Second, the deductive alignment with thematic coding was achieved with regard to the construct of Technology Acceptance Model and Diffusion of Innovation theory as opposed to the use of open-ended thematic analysis. The extracted findings were classified based on the perceived usefulness, perceived ease of use, and behavioural intention, relative advantage, compatibility, complexity, trialability, and observability. As an example, the information that relates to the optimization of revenues and predictive analytics was explained through the prism of perceived usefulness and relative advantage, whereas infrastructure limitations and skills deficit were explained through the prism of perceived ease of use and complexity. Such a systematic coding made it theoretically consistent and analytical. Third, an attempt was made to map the JKL in a comparative regional mapping in order to frame it within the greater patterns of AI diffusion. Urban destinations that were technologically advanced were compared to an emerging and peripheral tourism economies where the SME dominated and volatility in seasonal demand. This comparative exercise has revealed contextual differences that affect diffusion of innovation. Lastly, the synthesis of the coded findings into a comprehensive explanatory framework was done through a theory-based interpretation. Instead of enumerating opportunities and barriers separately, findings were interpreted as joint cognitive and structural factors that influenced the results of AI adoption. This interpretive synthesis changes the research type to descriptive review to analytical research based on innovation theory.

Limitations

Although it has tried to take care of the methodological rigor, various limitations should be noted. The research is based purely on secondary sources of data and this might not reflect the actual perceptions of the manager and operational specifics at the firm level that is unique to JKL. The lack of primary survey or interview-based validation inhibits the possibility of empirically measuring the behavioural intention and perceived usefulness of hotel managers in the region. Moreover, because of the limited availability of hotel level micro information, including specific financial performance measures or AI investment expenditure, granular analysis of return on investment relationships is constrained. Lastly, AI ecosystem is dynamic and technological capabilities, availability of infrastructure and patterns of adoption in the future are subject to change. The results should therefore be viewed as being contextually based but temporally constrained in the present phase of digital transformation. Findings and Analytical Discussion. The results are explained by the integrated Technology Acceptance Model and Diffusion of Innovation, which show that the perception of performance benefits, innovation attributes, and structural conditions are involved in the development of Artificial Intelligence adoption in the hotel industry of Jammu, Kashmir, and Ladakh. Instead of being an upgrade to the technology, AI adoption becomes a strategic choice that is mediated by managerial thinking, local infrastructure and organizational strength. Technology acceptance wise, it seems that perceived usefulness is the main factor of adoption intention. The AI-based revenue management system improves the availability of demand prediction, pricing optimization, and increases the occupancy performance. Predictive analytics employs strategic value in an area where the tourism season is strong and helps hotels to estimate the flow of pilgrimage and leisure travelers. In the same way, AI-based personalization systems improve the interaction with guests, providing them with personalized recommendations and automated communication, enhancing customer satisfaction and loyalty. Perceived usefulness is also supported by cost efficiency since automation of routine administrative processes like billing, check-in processes, and inventory control lowers the dependency on labor and lowers operational error rates. Predictive maintenance systems that track energy usage and equipment performance also play a part in the continuation of operations even in geographically challenging locations. These aspects together encourage managerial beliefs that AI has a direct effect in enhancing performance therefore boosting behavioural intention to adopt. To add to this point of view, diffusion attributes also describe the adoption patterns. Relative advantage can be observed in the fact that there is increasing awareness that AI-sourced services are increasing competitive positioning and service differentiation. With the move of national hotel chains to digital solutions and intelligent hotel management systems, the regional operators might view the technological modernization as the need to keep up with the market rivals. AI therefore is a process of operational resilience and strategic branding within competitive tourism markets.

Implications

The results produce significant theoretical, managerial, and policy implications by locating the AI adoption in a peripheral and infrastructure-sensitive tourism economy. The adoption of innovation frameworks facilitates the development of the study impacting the knowledge of the process of digital transformation in seasonality dominated, SME-dominant, and unequal infrastructure settings.

Theoretical Contributions

The study conducts an expansion of the innovation adoption theories outside of their typical use in urban and technology-advanced hospitality environment. It shows that cognitive factors like the perceived usefulness and perceived ease of use are largely influenced by structural factors, including the readiness of a digital infrastructure and the seasonality of tourism. The dynamics of adoption are hence situational, but not linear across the board. The study, further, brings in digital infrastructure of structural moderators, workforce capacity, institutional support, and seasonal demand fluctuation to the adoption model, and how the environmental factors play out with the perception and innovation qualities. The paper also gives some regional findings related to the AI diffusion in the hospitality economies dominated by mountains and SMEs that technological modernization is mediated through compatibility issues, financial risk, and operational constraints.

Managerial Implications

In the case of hotel managers, a gradual introduction of AI is more efficient compared to massive automation. Subsequent use, including the introduction of AI-based booking systems or revenue optimization software, is less expensive to deploy and trialable. The hybrid model of a human-AI service should be adopted in which automation is added to human-centric hospitality, not substituted. Skill training of the workforce also leads to less perceived complexity and enhanced long-term organizational flexibility.

Policy Implications

Infrastructure priority is extremely important at policy level. AI integration is based on the presence of reliable broadband connectivity and the creation of digital ecosystems. Pilot programs and other financial assistance mechanisms can be incentivized to make trialability more likely and minimise investment risk by SMEs. Training and institutional cooperation in the development of regional digital skills ecosystems will facilitate sustainable technological change, as well as lead to the overall economic modernisation.

CONCLUSION

The proposed study explored how Artificial intelligence (AI) can be adopted in the hotel sector in Jammu, Kashmir, and Ladakh (JKL) using a combined analytical model that incorporates the Technology Acceptance Model (TAM) and the Diffusion of Innovation (DOI) theory. Coming out of descriptive description of AI tools and automation trends, the study presented a systematic exposition of how the managerial perceptions, attributes of innovation, and structural conditions interrelate to influence technological adoption of a geographically peripheral and infrastructure-sensitive tourism economy. The results indicate that the adoption of AI in JKL is influenced mostly by the perceived usefulness, especially regarding the maximization of revenue, operational efficiency, personalization, and predictive maintenance. Managerial behavioural intention is reinforced in a tourism system with seasonality and competitive factors where the technologies to increase the accuracy of forecasting and tailoring services are involved. Simultaneously, DOI attributes, such as relative advantage and observability, can speed up the diffusion, particularly when regional players can notice successful implementation of digital by national chains and technologically progressive destinations. The process of adoption is however not linear or homogeneous. Perceived complexity, compatibility, and trialability are highly depended upon by structural moderators such as the digital infrastructure preparedness, SME preeminence, capacity limitations of workforce, and uncertainty of money. These contextual influences mediate diffusion patterns and determine the fact that integration of AI in JKL is slow and selective and not fast and extensive. The paper thus points out that technological change in the peripheral tourism economies is dependent on the infrastructural stability, institutional support, and organizational preparedness. In theory, the study builds upon the body of innovation adoption by introducing structural moderators in TAM-DOI framework and proves that cognitive determinants cannot be used to explain the results of diffusion in infrastructure-constrained areas. The study fills an essential gap in literature since most existing research is concentrated in urban areas, which leaves the adoption of AI as a hospitality technology in a mountainous and seasonally unstable ecosystem with a significant gap of knowledge. The results are added to the context-sensitive comprehension of digital transformation in the emerging touristic areas. This framework should be developed further by conducting future research grounded on empirical validation that uses primary data. Generalizability would be strengthened by survey-based research into the usefulness and ease of use, qualitative research into the compatibility of cultures, and longitudinal research into the diffusion patterns. The comparative analyses between metropolitan and peripheral destinations would also help to shed more light on contextual differences in the dynamics of AI adoption. With the development of digital ecosystems and the enhancement of infrastructure, further investigations will be necessary to comprehend the way peripheral hospitality systems will be negotiated to modernize technology without losing the authenticity of services and the resilience of the region.

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