Int. J. Hum. Capital Urban Manage., 9(1): 29-46, Winter 2024

International Journal of Human Capital in Urban Management
(IJHCUM)

Homepage: http://www.ijhcum.net/

ORIGINAL RESEARCH PAPER

Adoption intention of artificial intelligence enabled smart city services from citizens' perspective

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ARTICLE INFO

Article History:
Received 11 July 2023
Revised 27 September 2023
Accepted 16 October 2023

Keywords:
Artificial intelligence
Ethics
Smart City citizen services
Technology adoption

DOI: 10.22034/IJHCUM.2024.01.03

ABSTRACT

BACKGROUND AND OBJECTIVES: Urban administrators of major cities in India are planning to deploy advanced information technologies such as artificial intelligence to deliver e-governance services. It is expected to enable citizens to acquire relevant information to their commonly asked question without significant technological expertise. With its text, speech, and image processing capabilities similar to human beings, artificial intelligence is predicted to have both positive and negative social impact. The objective of this paper was to develop a conceptual framework consisting of enablers and barriers in adopting artificial intelligence enabled service delivery in a smart city from citizens' perspectives. The study is novel in terms of empirically finding factors influencing adoption intention of artificial intelligence for availing citizen services in a nation like India which has a very large population and developing economy.
METHODS: The study utilized an extended unified theory of acceptance and use of technology framework and employed survey-based data collection technique. A structured survey was circulated as part of primary data collection. The responses were collected from 772 sample respondents from three upcoming smart cities in India and were further examined by deploying the structural equation modeling technique using IBM SPSS and AMOS tools.
FINDINGS: The proposed framework in this research study has social implications in terms of key factors that are critical when conceptualizing government services using artificial intelligence to avoid any harmful effects on society. The findings demonstrated six enablers and three barriers significantly affecting adoption intention ($p<0.05$) and explained 81 percent of the variance (R2) with the model's Goodness-of-fit index above 0.9. The quantitative results are also validated with the case studies from six smart cities across the globe for designing and deploying artificial intelligence-based services in the public sector.
CONCLUSION: The study highlights that the smart city management must make sufficient effort to ensure that artificial intelligence service delivery in a smart city is equitable for all socioeconomic levels of city residents. The study provides several policy recommendations for governments and technology service providers when deploying artificial intelligence-based services for citizens in developing countries like India.

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
51	2	6

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Note: Discussion period for this manuscript open until Aptil 1, 2024 on IJHCUM website at the "Show Article.

INTRODUCTION

India is one of the world's fastest-growing economies, with an estimated 35 percent (%) of its population living in cities (World Bank, 2022). However, unplanned urbanization has resulted in multiple issues from both government and residents point of views. Therefore, in 2015, the Indian government announced the ambitious Smart Cities Mission to improve quality of life and foster economic growth in top 100 cities across the country. This transformation is expected to be achieved by utilizing the latest breakthroughs in Information and Communication Technologies (ICTs) (Drobyazko *et al., 2023*; Praharaj *et al.*, 2018). With the help of ICTs, the smart city initiative aims to move away from an unplanned urbanization to a planned urbanization (Zeng *et al.*, 2016). As metropolitan areas expand and city resources become scarce, new problems arise, such as traffic congestion, waste disposal, safety, and the allocation of shared space, among others (Kuberkar and Singhal, 2020). Cities are therefore progressing toward becoming smarter. Across the globe, local councils, private businesses, and research institutes are launching several initiatives to modernize urban areas and build smart cities (Camero and Alba, 2019). Smart city is generally imagined by merging advanced ICTs with public administration processes (Bibri and Krogstie,2018). In contrast to a traditional urban neighborhood, a smart city is expected to provide intelligent services that improve the quality of life and enable social sustainability (Marvi *et al.*, 2023) and economic growth (Caragliu *et al.*, 2011). Technology adoption in government, popularly known as e-governance, eases not only civic operations internally but also improves external service delivery to citizens (Yeh, 2017). However, in 2020, UN ranked India at 100th position in e-government development index and 29th position in e-participation index (UN, 2020) which is a cause of concern for a developing and large country like India.

Role of AI in smart cities

To create their own ideal smart city, common people are expected to participate in the urban reforms and monitor municipal governance (Bednarska-Olejniczak *et al.*, 2019). There are various traditional and advanced ICTs that have the potential to be deployed in a smart city (Chatterjee and Kar, 2018; Nam and Pardo, 2011). From the current set of emerging technologies, Artificial Intelligence (AI) is showing promise to completely overhaul services through automation, intelligent forecasting, and transparency. In AI, machines are programmed to learn, comprehend, and solve problems in the same manner as humans do (Minsky, 1961). Recent development in Generative AI, a subcategory of AI domain, has increased its awareness amongst population and expanded use cases many-fold. The National Institution for Transforming India (NITI) Aayog, a government of India policy think tank, anticipates that smart cities will be one of the most important application areas for AI, which, if applied correctly, will resolve several long-standing problems in civic operations (NITI Aayog, 2018). However, widespread adoption of innovative technology requires time and follows an adoption curve (Lee *et al.*, 2013). It is important to note that AI is an emerging technology, and it differs from traditional technologies in terms of user experience, cost to deploy, and algorithmic complexities (Kuberkar *et al.*, 2022). Also, data is the backbone to AI and India lacks data governance standards (Lnenicka and Saxena, 2021). Moreover, there are no widespread, long-term actual usage patterns of AI by ordinary people in India. In brief, there is a need for additional research on the possible application of such advanced technologies in e-governance (Ølnes and Jansen, 2017). Andrew Ng, a former leader of Google Brain and Baidu's AI business, compares AI to electricity, a century-old transformative technology (Ng, 2018). In the administration of municipal corporations, AI has begun to acquire traction. It can result in higher efficiencies in smart cities, such as better traffic management, energy, and water distribution, and ultimately make cities more sustainable (NITI Aayog, 2018). While AI offers many advantages to public-sector services, it also has a few disadvantages as pointed out by several researchers. The trade-off between the possible harm the AI system can do, and the potential benefit it can provide must be thoroughly examined (Siau and Wang, 2020; Zajko, 2021). There could be few AI solutions that are competent and efficient, but in practice, they could become biased and unexplainable (Nevala, 2017; Yang *et al.*, 2022). This requires further studies to better understand AI's implications to city residents more holistically.

Theoretical foundation

As the purpose of this study is to examine the determinants of AI's adoption intention in a smart city, the theories pertaining to technology adoption by individuals are of relevance. More than 100 publications from reputable peer-reviewed journals were analyzed to determine the current state of AI technology and emerging technology adoption by individuals in a smart city. The theoretical literature review is performed on the following subtopics: (1) Smart City Literature; (2) AI Literature; and (3) Theories of Technology Adoption. Contemporary social scientists consider population density and spatial heterogeneity to define a city. The city could also be defined as a type of community-based on markets, specific laws, and political autonomy. Technological improvements have a substantial impact on the industrialization capability of cities, which in turn influences and is influenced by other social institutions such as family, social class, and politics (Sjoberg, 1955). Smart cities are the application of smart technologies such as AI to the social and economic operations of a city. Arthur Samuel Lee coined the term "machine learning" in his revolutionary work in computer games and artificial intelligence to describe the process of making computers function. Initially, AI was limited to imitating human intelligence, but it has now evolved into a much broader notion that may assist in a variety of occupations (Dwivedi *et al.*, 2021). Rapid advances in information technology have drawn a large number of scholars interested in examining the elements underlying adoption intent and actual usage of technology-led solutions. Ajzen introduced the theory of planned behavior (TPB) after Fishbein and Ajzen introduced the theory of reasoned actions (TRA). These theories serve as the basis for measuring the intent to accept technological solutions. Davis extended TRA and TPB to develop a basic yet powerful TAM theory for measuring adoption intention and subsequent use of technology solutions. Venkatesh et al. further evolved TAM into the Unified Theory of Acceptance and Use of Technology (UTAUT) theory (Venkatesh *et al.*, 2003).

Research gap

In recent years, research has been conducted on the determinants e-governance adoption in various countries (Almaiah and Nasereddin, 2020). AI has a potential to significantly change the public sector service delivery. However, there are negligible studies in the domain of AI's adoption in public sector. Since India is on the path of building smart cities with a focus on using AI, it is appropriate to examine the determinants of AI technology adoption in civic service delivery from the citizens' perspective. Such a study would provide guidelines for the usage of AI in urban administration. Therefore, the following research question is addressed in this study: Which factors influence the adoption intention of AI in the delivery of municipal services within an India smart city? The study answers this research question by using an extended Unified Theory of Acceptance and Use of Technology (UTAUT) and performing quantitative analysis on the primary data collected through surveys in the Maharashtra state of India between February and May of 2023. Maharashtra is the most advanced state in India in terms of education and economy. Finally, the study is novel in terms of empirically finding factors influencing adoption intention of AI while availing municipal service in a nation like India which has a large population, limited resources, and a developing economy. The proposed framework in this study has social implications in terms of key factors that are critical when conceptualizing government services using AI to avoid any harmful effects on society.

MATERIALS AND METHODS

Conceptual Framework

The aforementioned concerns like technology novelty and its potential risks and benefits in e-governance falls under the broader umbrella of information systems research and studies have been conducted for incumbent technologies using various technology adoption theories (Lai, 2017). Studying adoption intention prior to actual usage for emerging technologies and designing products and services according to factors that influence adoption intention increases the likelihood that the technology will be utilized successfully in the future (Kupfer *et al.*, 2016). From the available technology adoption theories, the UTAUT model is chosen as the base theoretical foundation for this research. Prior meta-analyses have demonstrated that UTAUT is a credible model that reliably explains a substantial proportion of the intention to adopt novel technologies (Dwivedi *et al.*, 2019). In addition, it acquired robust

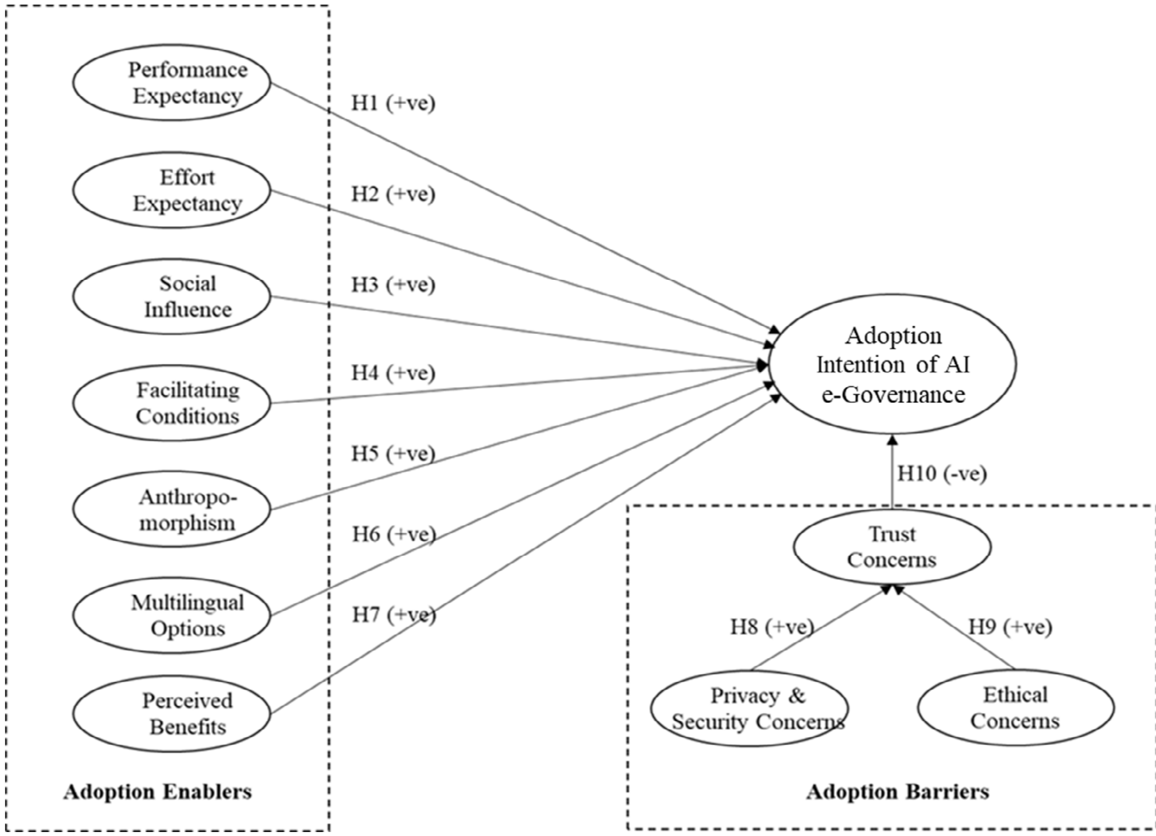

Fig. 1: Hypothesized AI4SC framework of the study

empirical evidence from global academics for its use in e-governance adoption by citizens (Pillai and Sivathanu, 2020). Based on the literature study, the researchers of this study have proposed an extended UTAUT model (Fig. 1) to identify enablers and barriers to AI adoption in a smart city, named as AI4SC framework. According to the UTAUT theory, technology adoption (ADIN) is contingent on Performance Expectancy (PEXP), Effort Expectancy (EEXP), Social Influence (SINF), and Facilitating Conditions (FCND) (Venkatesh *et al.*, 2003).

It was found from literature studies that UTAUT alone is not sufficient to explain the variance in adoption intention and other technology and culture related factors also influence the desire to use the technology. Therefore, the researchers of this study have included additional factors such as Anthropomorphism (ANTH), Multilingual Option (MLOP), Perceived Benefits (PBEN), Privacy and Security Concerns (PSEC), Ethical Concerns (ETHC), and Trust Concerns (TSTC) in the proposed AI4SC model based on AI's technology characteristics and potential social impact.

The hypotheses that make up the conceptual model are as follows:

Relationship between PEXP and ADIN: The PEXP is described as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh *et al.*, 2003). This means newer technological systems should be appropriate, efficient, and beneficial to access citizen services, just like any other new technology-enabled system. It has been noted that, even in cases when an online application is submitted, there are still some online municipal corporation services that are only partially available online and need residents to physically visit the office in order to receive the service. Hence, the suggested system should offer all the features needed to access the service in its entirety. Several prior researchers have demonstrated that PEXP favorably impacts ADIN of online government services (Gupta *et al.*, 2016), and it is anticipated that this relationship will remain true for AI adoption in a smart city. Thus, the researchers of this study hypothesize that:

H1: *PEXP positively affects ADIN*

Relationship between EEXP and ADIN

The EEXP is described as "the degree of ease associated with the use of the system" (Venkatesh *et al.*, 2003). In the urban context of an Indian metropolis, it is commonly observed that a segment of the population possesses advanced qualifications and a high level of technological literacy, whilst another segment of society exhibits limited literacy skills and lacks familiarity with technology. Therefore, the proposed system is expected to be low complex, making it easily comprehensible and acquirable. The provision of unambiguous instructions by the system is crucial in mitigating the digital gap within society. Past research has indicated that EEXP is positively correlated with the use of online government services (Rana *et al.*, 2017), and it is anticipated that a similar relationship will exist between EEXP and the adoption of AI in a smart city. Hence, the researchers of this study hypothesized:

H2: *EEXP positively affects ADIN*

Relationship between SINF and ADIN

SINF is described as "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh *et al.*, 2003). As individuals witness the adoption of new technology by their acquaintances, family members, and other members of their social network in order to access municipal services, it is likely that they too will begin to embrace citizen services that are facilitated by novel technology solutions. SINF is believed to have had a positive impact on the ADIN of online public administration services in the past (Rana *et al.*, 2017), and it is anticipated that the same will be true for the adoption of AI in a smart city. Thus, the researchers of this study hypothesize that:

H3: *SINF positively affects ADIN*

Relationship between FCND and ADIN

The FCND is described as "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" (Venkatesh *et al.*, 2003). In order to access online municipal services, it will be necessary for citizens to have continuous connectivity available to them at all times. Hence, it is believed that making a concerted efforts to ensure the provision of internet connectivity to all geographical regions encompassing the city to enable residents from every ward and socio-economic stratum to avail themselves of the many online services. FCND has been found to positively correlate with the adoption of online government services (Gupta *et al.*, 2016), and it is anticipated that the same will be true for the adoption of AI in a smart city. Hence, the researchers of this study hypothesized:

H4: *FCND positively affects ADIN*

Relationship between ANTH and ADIN

ANTH is defined as "assigning human characteristics to nonhuman objects such as learning and reasoning". AI technology enables systems to exhibit human-like behavior. AI-based robots exist in both software and physical forms. The uncanny valley theory is frequently used to examine ANTH as it relates to the adoption of robotic technologies. The conventional form of interpersonal communication between individuals is considered inherent, and there is a generally comprehensive understanding of the elements of empathy, emotions, and contextual factors involved. Robotic conduct is observed when a system operates devoid of empathetic consideration for the end-user or lacks comprehension of the contextual nuances associated with a service request. Researchers in the past have presented the uncanny valley hypothesis, which proposes that humans are generally receptive to ANTH-rich systems (Pillai and Sivathanu, 2020). It is anticipated that the same will hold true for AI adoption in the smart city. Hence, the researchers of this study hypothesized:

H5: *ANTH positively affects ADIN*

Relationship between MLOP and ADIN

The MLOP analyzes the impact of employing a technology solution in multiple languages to complete a task (Singh *et al.*, 2005). India is a nation characterized by its linguistic diversity. A significant portion of the population lacks proficiency in the English language, either in terms of literacy or fluency. The field of technology has seen advancements to facilitate the utilization of many languages. Several states in India are actively advocating for the utilization of indigenous languages in the provision of government services. Similarly, AI adoption in smart city is expected to be influenced by MLOP. Thus, the researchers of this study hypothesize that:

H6: *MLOP positively affects ADIN*

Relationship between PBEN and ADIN

PBEN refers to an individual's belief that technology will provide economic or non-economic benefits. Offering incentives or prizes is a viable strategy for modifying the behavior of end-users. ICT technologies have a multitude of advantages as compared to conventional in-person or online services. Furthermore, the implementation of monetary incentives or other forms of rewards could potentially expedite the adoption of the new system. In the context of online services, there are direct and indirect advantages. Immediate and practical benefits of utilizing an ICT system include a monetary gain, greater working speed, and increased information accessibility (Lee, 2009). Indirect advantages include less obvious benefits, such as accessibility, 24-hour service, and alternatives for value-added services. Researchers in the past found that PBEN had a positive effect on behavioral intention to use technology solutions (Gupta *et al.*, 2016). PBEN is expected to perform similarly for AI adoption in a smart city. Hence, the researchers of this study hypothesized:

H7: *PBEN positively affects ADIN*

Relationship between PSEC and TSTC

PSEC is a significant impediment to the ADIN of online government services (Yang *et al.*, 2019). PSEC consists of both online privacy concerns and security concerns. Privacy concerns are the individual's concerns regarding threats to data privacy, while security concerns relate to an individual's perception of the overall security of the system against illegal access and fraud. The objective of e-governance systems is to enhance online safety. Although some cities have implemented online government systems, the primary obstacles to their widespread acceptance are the apprehensions surrounding data privacy and system security. In order to enhance public trust in the planned AI4SC system, it is imperative to ensure the protection of people' privacy and security. The PSEC contributed to a decline in public trust, as observed in past studies, and is expected to behave in a similar manner for information systems for citizen services (Kuberkar and Singhal, 2021). Thus, the researchers of this study hypothesize that:

H8: *PSEC has a positive relationship with TSTC*

*Relationship between ETHC and TST*C

Ethics is considered as an individual's judgment that a technological system complies with social and moral standards (Acman and Mishra, 2017). In this research, questions of fairness, accountability, openness, and moral principles are addressed by ETHC. There exists a potential for the introduction of bias into algorithms within the setting of a smart city, leading to outcomes that exhibit preferential treatment or adverse consequences towards specific groups. The presence of undetected data bias or lack of accountability has the potential to undermine the trust on the robust solution. In order to enhance confidence, it may also be imperative to employ concepts of Explainable Algorithms that effectively demonstrate the concept of transparent decision and outcomes by a system. Moreover, individuals tend to adopt technology that reduces risks and does not disrupt social peace. Higher ETHC has been shown to decrease trust in information systems (Kuberkar *et al.*, 2022) and is anticipated to exhibit similar behavior to AI adoption in a smart city. Hence, the researchers of this study hypothesized:

H9: *ETHC positively affects TSTC*

Relationship between TSTC and ADIN

Trust is an individual's faith in the dependability of a technological solution with reduced uncertainty. The measurement of citizens' trust when using online government services can be assessed based on their judgments of the absence of risks, uncertainties, or fraudulent activities during the course of a transaction. TSTC includes trust-related concerns while working with online systems in this study. It has been demonstrated that decreased TSTC increases the adoption of online information systems (Lewis *et al.*, 2018). A number of previous studies on trust have investigated the risk that an individual assumes when relying on new technology to achieve goals. The anticipated rise in the acceptance and utilization of online citizen services within smart cities could be contingent upon people perceiving a minimal level of danger associated with engaging with the system. Therefore, a higher TSTC may necessitate more frequent intervention or monitoring of the system's performance. This study, like previous research (Følstad *et al.*, 2018), assumes that citizen TSTC may play an important role in the adoption of AI in a smart city. Thus, the researchers of this study hypothesize that:

H10: *TSTC negatively affects ADIN*

Survey design and data collection

The hypothesized framework is translated into a simple-to-understand survey questionnaire consisting of questions related to the potential factors influencing citizens' intentions to adopt AI4SC. The questionnaire was evaluated from a panel of five experts. All construct-related items in the survey were graded on a five-point Likert scale. Likert scale Respondents were instructed to select the choices from the range of 1 to 5 (with 1 indicating strong disagreement; 2 disagreement; 3 neutrality; 4 agreement; and 5 strong agreement). Based on study's objective and research method, Likert scale helps to measure extent to which respondents agree or disagree on the items affecting their adoption intention of technology. In the pilot phase before mass survey, Dillman's (2000) technique of four stages of questionnaire item testing was utilized. The online survey was created using Google forms and distributed to 58 participants (i.e., greater than 10 percent of the minimal sample size) employing convenience sampling to ensure the questionnaire's wording and contextual clarity. Pilot respondents reviewed the questionnaire and provided suggestions for enhancements, such as the questionnaire wording, addition of relevant images, and the reduction of the variables survey questions from 41 to 36 questions, as shown in Table 1. The target demographic for this research study consists of all residents of India's designated 100 smart cities. Due to practical constraints, the researcher could only collect data from three smart cities: Pune, Pimpri-Chinchwad, and Thane. The sample cities consist of population drawn from various parts of the country because of the presence of industry cluster and resulting migration. It helps in reducing cognitive bias due to small set of sample cities. According to the 2011 Census, the population under study is roughly 6.7 million (Census of India, 2011).

As per the nature of this study, the researchers of this study recruited individuals employing a combination of purposive and snowball sampling strategies. In addition, the researchers of this study assumed that people aged 25 to 60 with at least 15 years of formal education would have used internet-enabled technology for at least five years in the selected smart cities. Selecting these set of respondents ensures representation of population as mostly working people in this age group are major consumers of various municipality services. People aged below 25 years typically falls into student category while above 60 years falls into retired category. Hence, the study does not suffer from generalizability of findings. Consequently, the sample unit of this research study was a person aged 25 to 60 with at least a high school diploma or bachelor's degree who utilizes an internet-enabled gadget for employment or to access services from private or government organizations. According to the Cochran's sample size formula, the minimum sample size for the quantitative phase should be 385 for a 95% confidence interval with a 5% margin of error for the population under research. In addition, most research employing SEM implies that a sample size of 10 for each item is a sufficient estimate. A study by Irani *et al.* (2012) found that approximately 87% of the e-governance adoption studies in leading journals were done with a sample size below 750. Hence, a sample size greater than 750 would be deemed more than adequate for the current investigation based on the findings of several studies with similar objectives. As a result, the researchers of this study decided to recruit approximately 900 participants for this study, estimating that 10 to 15% of responses would be invalid or incomplete. In actuality, the researchers of this study only obtained 867 responses. The incomplete survey responses were eliminated, leaving a final survey with 772 responses for analysis.

Table 1: Survey question items

Parameter	Question	Variable	References
Performance Expectancy (PEXP)	It may provide flexibility while availing services	PEXP1	Venkatesh *et al.*, 2003
	It may deliver citizen services on-time	PEXP2	
	It may be developed with citizen needs in mind	PEXP3	
Effort Expectancy (EEXP)	It may deliver service fully in online mode	EEXP1	Venkatesh *et al.*, 2003
	It may reduce efforts to visit multiple departments	EEXP2	
	It may be easily understandable	EEXP3	
Social Influence (SINF)	My friends and family may expect me to use it	SINF1	Venkatesh *et al.*, 2003
	My social circle or people in my society may use it	SINF2	
	People whom I follow may influence my adoption	SINF3	
Facilitating Conditions (FCND)	I may have resources (phone or computer) to use it.	FCND1	Venkatesh *et al.*, 2003
	I expect availability of help centers in my area or locality	FCND2	
	I will have internet connectivity to access the system	FCND3	
nthropo-morphism (ANTH)	System interaction may be similar to human staff.	ANTH1	Pillai and Sivathanu, 2020
	It may understand context of my service request	ANTH2	
	The system may not be robotic	ANTH3	
Multilingual Option (MLOP)	It is ok if it communicates only in English language	MLOP1	Singh *et al.*, 2005
	It may work in local or Hindi language as well	MLOP2	
	I may be comfortable when it works in native language	MLOP3	
Perceived Benefits (PBEN)	It may provide monetary benefits like discounts	PBEN1	Gupta *et al.*, 2016
	It may reward me if I follow all city norms and rules	PBEN2	
	It may provide badge for my usage of new system	PBEN3	
Privacy and Security Concerns (PSEC)	I may worry about my private data sharing	PSEC1	Yang *et al.*, 2019
	I expect system and data may be secure	PSEC2	
	It may not capture my data without my permission	PSEC3	
	My data may be shared only when I authorize	PSEC4	
Ethical Concerns (ETHC)	It may deliver services in fair and ethical way	ETHC1	Kuberkar *et al.*, 2022
	Govt may inform how the system is designed	ETHC2	
	Someone may be accountable for mistakes	ETHC3	
	I expect clear responsibility and legal options	ETHC4	
Trust Concerns (TSTC)	I may not use it if it makes mistakes	TSTC1	Lewis *et al.*, 2018
	It may deliver service in dependable manner	TSTC2	
	It may provide reliable service without any issues	TSTC3	
Adoption Intention (ADIN)	I may like the idea of such an automated robotic system	ADIN1	Venkatesh *et al.*, 2003
	When ready, I may intend to use the system	ADIN2	
	Using it may be a pleasant experience	ADIN3	
	I may recommend others to use the system	ADIN4	

RESULTS AND DISCUSSION

A set of statistical tests were conducted on the collected survey responses, and the findings are summarized in this section. Initial data cleansing process consisted of removing errors, incomplete responses, and outliers. After data cleansing, data normalization was evaluated. Subsequently, the validity and reliability of the data have been confirmed. Finally, Confirmatory factor analysis (CFA) and Structural Equation Modeling (SEM) tests were conducted to test the hypotheses. CFA assists in testing validity of factor structure while SEM assists in evaluating multivariate causal relationship between factors of a model.

Measurement model analysis

CFA was performed using IBM SPSS V28 (Fahimah *et al.,* 2023). All 36 independent variables were initially included in the CFA, generating ten factors that explained approximately 70.4% of the total variance. Utilizing PCA (Principal Component Analysis) with Varimax rotation, the data was extracted. According to the findings of the measurement model, the Kaiser–Meyer–Olkin (KMO) value was 0.897, which exceeded the minimum suggested value of 0.5 (Hair *et al.*, 2006). Moreover, Barlett's sphericity test proved significant at the 0.01 level (p 0.000). By examining the factor loadings, it became evident that each of the ten factors loads correctly into its own factor group. Table 2 indicates additional statistical

Table 2: Confirmatory factor analysis results: factor loadings and reliability

Latent variable	Observed variable	Standardized factor loading	Cronbach's Alpha	VIF
PEXP	PEXP1	0.850	0.906	1.618
	PEXP2	0.914		
	PEXP3	0.858		
EEXP	EEXP1	0.782	0.883	1.819
	EEXP2	0.900		
	EEXP3	0.857		
SINF	SINF1	0.894	0.879	1.033
	SINF2	0.935		
	SINF3	0.702		
FCND	FCND1	0.807	0.887	1.865
	FCND2	0.851		
	FCND3	0.892		
ANTH	ANTH1	0.840	0.871	1.739
	ANTH2	0.825		
	ANTH3	0.838		
MLOP	MLOP1	0.861	0.890	1.424
	MLOP2	0.849		
	MLOP3	0.860		
PBEN	PBEN1	0.664	0.853	1.237
	PBEN2	0.858		
	PBEN3	0.911		
PSEC	PSEC1	0.873	0.913	1.549
	PSEC2	0.860		
	PSEC3	0.851		
	PSEC4	0.820		
ETHC	ETHC1	0.853	0.909	1.467
	ETHC2	0.851		
	ETHC3	0.855		
	ETHC4	0.823		
TSTC	TSTC1	0.867	0.907	1.680
	TSTC2	0.903		
	TSTC3	0.855		
ADIN	ADIN1	0.787	0.843	1.438
	ADIN2	0.606		
	ADIN3	0.867		
	ADIN4	0.822		

Table 3: Construct validity measures - convergent validity and discriminant validity

Construct	CR	AVE	MSV	ASV	PEXP	EEXP	SINF	FCND	ANTH	MLOP	PBEN	PSEC	ETHC	TSTC	ADIN
PEXP	0.907	0.765	0.417	0.214	0.875										
EEXP	0.884	0.719	0.510	0.244	0.574	0.848									
SINF	0.885	0.722	0.011	0.002	0.041	0.014	0.849								
FCND	0.887	0.724	0.518	0.256	0.430	0.531	-0.021	0.851							
ANTH	0.873	0.696	0.449	0.242	0.471	0.593	0.013	0.583	0.834						
MLOP	0.892	0.734	0.375	0.182	0.457	0.493	-0.047	0.433	0.432	0.857					
PBEN	0.856	0.669	0.263	0.138	0.369	0.468	0.050	0.404	0.367	0.384	0.818				
PSEC	0.913	0.725	0.362	0.185	-0.419	-0.462	0.029	-0.484	-0.516	-0.384	-0.287	0.852			
ETHC	0.909	0.715	0.457	0.220	-0.469	-0.487	-0.034	-0.633	-0.518	-0.413	-0.307	0.431	0.846		
TSTC	0.908	0.766	0.502	0.208	-0.495	-0.500	0.106	-0.499	-0.444	-0.387	-0.367	0.423	0.403	0.875	
ADIN	0.857	0.603	0.518	0.386	0.646	0.714	0.042	0.720	0.670	0.612	0.513	-0.709	-0.602	-0.676	0.776

measurements demonstrating that all constructs possess an adequate level of reliability. The CFA determined that eleven variables accounted for 64.36 percent of the total variation. Cronbach's alpha coefficients are used to measure internal consistency, with a value above 0.7 being considered adequate (Nunnally, 1994). The factor loadings and Cronbach's alpha exceed the permissible limits, confirming the construct's reliability requirements. The Variance Inflation Factor (VIF) was calculated for each latent variable for testing the multicollinearity. The VIF of each variable is found to be less than 2.5, indicating that there is no multicollinearity in the constructs.

Construct validity

Composite Reliability (CR) indicates latent variable's consistency and reliability. Convergent validity, measuring related items convergence, was determined using Average Variance Explained (AVE). The CR values should be greater than 0.7, and the AVE should be larger than 0.5 (Hair *et al.*, 2006). It is also recommended that Maximum Shared Variance (MSV) should be less than AVE and Average Shared Variance (ASV) should be less than AVE as well. Both CR and convergent validity is established, and the values are summarized in Table 3. Discriminant validity, measuring the uniqueness of latent variables, is tested by examining correlations between latent variables (Henseler *et al.,* 2015). To verify discriminant validity using Fornell-Larcker criteria, off-diagonal values were computed, and AVE was compared to the intercorrelation of the construct. Table 3 indicates that the shared variance values were less than the square root of AVE, demonstrating the discriminant validity of the research constructs (Tajpour and Razavi, 2023; Samimi, 2024).

Structural model analysis

Using SEM, the relationship between latent variables is estimated. AMOS V26 is employed to compute a variety of parameters. Table 4 summarizes the goodness-of-fit indices which demonstrates that the observed sample values match with expected population under normal distribution (Samimi *et al.,* 2023).

After establishing goodness-of-fit measures, SEM analysis followed. Table 5 shows the results of hypotheses testing from SEM analysis and Fig. 2 shows the validated AI4SC conceptual model. The hypotheses test results are as follows: H1: The tests

Table 4: Goodness-of-fit measures for SEM model

Goodness-of-fit Indices	Recommended value	SEM model
Chi-square (CMIN)	-	1073.438
Degrees of freedom (DF)	-	548
P value	<0.05	0.000
CMIN/DF	1-3	1.959
Goodness of fit index	>=0.9	0.902
Adjusted goodness of fit index	>=0.8	0.834
Comparative fit index	>=0.9	0.948
Tucker Lewis index	>=0.9	0.940
Root mean square error of approximation	<=0.05	0.049

Table 5: Hypothesis testing results and structural relationships

Hypothesis	Path	Path coefficient (β)	SE	p-value	Decision
H1	PEXP → ADIN	0.14	0.029	0.001**	Supported
H2	EEXP → ADIN	0.17	0.043	0.000***	Supported
H3	SINF → ADIN	0.07	0.023	0.021*	Supported
H4	FCND → ADIN	0.27	0.036	0.000***	Supported
H5	ANTH → ADIN	0.14	0.036	0.004**	Supported
H6	MLOP → ADIN	0.17	0.030	0.000***	Supported
H7	PBEN → ADIN	0.06	0.042	0.232^{ns}	Not Supported
H8	PSEC → TSTC	0.32	0.057	0.000***	Supported
H9	ETHC → TSTC	0.30	0.059	0.000***	Supported
H10	TSTC → ADIN	-0.32	0.026	0.000***	Supported

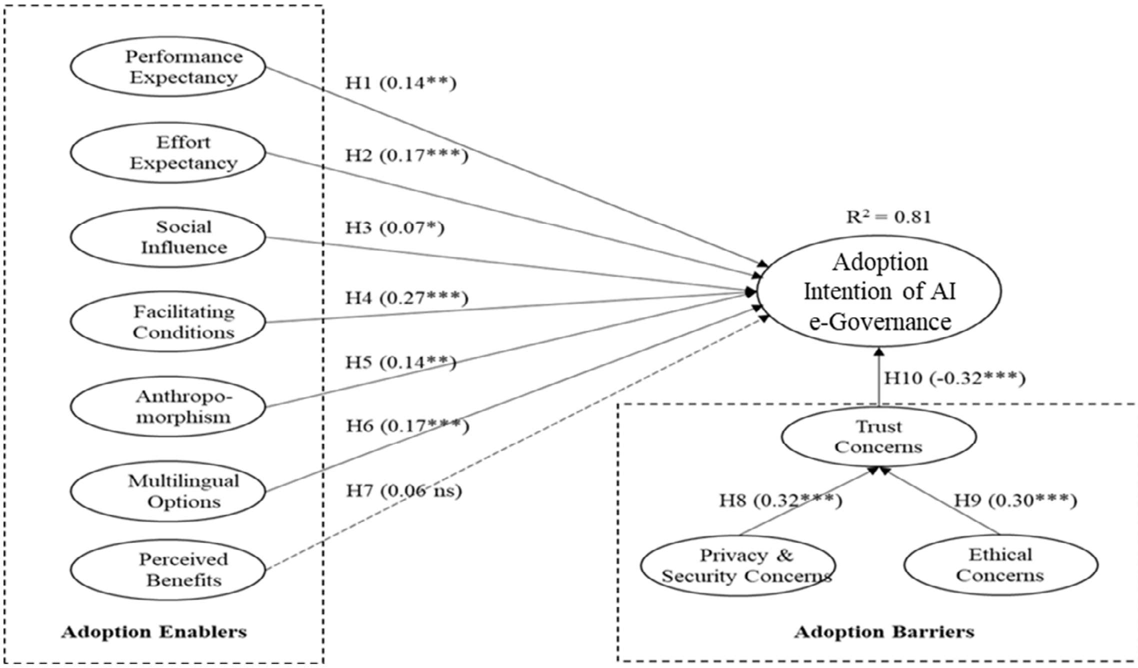

Fig. 2: SEM results of the proposed AI4SC model

revealed that PEXP had a significant impact (β = 0.14 and p=0.001) on the ADIN. Thus, the H1 is supported indicating that citizens feel the AI4SC system would enhance the performance of citizen service delivery, thereby increasing the likelihood of AI adoption.

H2: The results of this study prove that EEXP had a significant impact (β = 0.17 and p=0.000) on the ADIN. Therefore, the H2 is supported, highlighting that the citizens view AI4SC to be an easy-to-use system for availing online municipal corporation services in an SC (Rana *et al.*, 2017). H3: The study found that SINF had a significant (β = 0.07 and p=0.021) impact on the ADIN, suggesting that individuals tend to imitate their peers when it comes to adopting new technology such as the proposed AI4SC. Thus, H3 is supported. H4 investigated the influence of FCND on the ADIN of AI4SC. H4: The results indicate that FCND had a significant impact (β = 0.27 and p=0.000) on the ADIN. Thus, H4 is supported, highlighting that the citizens perceive AI4SC will be a viable option for public services because they would have the necessary infrastructure, such as internet connectivity, electronic devices, or physical help centers in their local wards, to access the services (Gupta *et al.*, 2016). H5: The findings of the study demonstrate that ANTH had a significant influence (β = 0.14 and p=0.004) on the ADIN, suggesting that anthropomorphism, or human-like features, are crucial for the adoption of the AI4SC system by the ordinary citizens. Consequently, H5 is supported (Pillai and Sivathanu, 2020). H6: The tests revealed that MLOP had a significant effect (β = 0.17 and p=0.000) on the ADIN. Thus, H6 is supported, emphasizing that citizens want AI4SC to deliver services in multiple languages for effective use of online municipal corporation services without the burden of language translation (Singh *et al.*, 2005). H7: The research indicates that PBEN had no substantial impact (β = 0.06 and p=0.232) on the ADIN, meaning that individuals do not anticipate additional tangible or intangible benefits while utilizing AI4SC to access municipal services. Thus, H7 is not supported. The non-significance of this hypothesis in this research study may be attributed to the existing status of government services, which are marked by delays and mistakes. Therefore, citizens may not be anticipating extra direct or indirect benefits from AI4SC beyond those already considered factors. H8: According to the data analysis, PSEC had a significant effect (β =

0.32 and p=0.000) on TSTC. Thus, H8 is supported. The finding emphasizes that implementing AI for citizen services within an SC requires rigorous data privacy and security considerations (Yang *et al.*, 2019). H9: The evidence indicates that ETHC had a significant effect (β = 0.30 and p=0.000) on the TSTC. Thus, H10 is supported indicating that citizens believe that AI-based public sector systems should be built on ethical principles such as proper accountability, minimal bias, increased transparency, and adherence to moral values (Kuberkar *et al.*, 2022). H10: The research suggests that TSTC had a significant impact (β = -0.32 and p=0.000) on the ADIN, indicating that individuals are ready to adopt an AI-enabled system when it is reliable, risk-free, and trustworthy. Thus, H10 is supported (Følstad *et al.*, 2018; Lewis *et al.*, 2018).

Results validation with global urban AI initiatives

The researchers of this study have compared the study findings with some of the leading metropolitan cities in the world which have taken AI initiatives for urban governance (Table 6). The secondary data is collected from various authentic web sources and research articles on the five cities, namely, Toronto, Helsinki, Dubai, Singapore, and Melbourne.

The research demonstrates the differences between AI and other types of technologies, highlighting the need for additional research into AI-specific components, especially for broader societal implications. Being relatively nascent technologies, the academic literature currently lacks detail understanding of how ordinary citizens perceive AI technical solutions for civic operations. Therefore, the researchers of this study proposed a novel AI4SC framework to investigate the factors that will influence the adoption of AI technologies in smart city. More specifically, this research validates that UTAUT is still the relevant base theoretical model to study technology adoption in the public sector. The study brought together seven enablers and three barriers from the individual (PEXP, EEXP, PBEN, TSTC), technical (FCND, ANTH, MLOP, PSEC), and social (SINF, ETHC) domains to study the adoption intention (ADIN). While the study found that the basic four UTAUT factors are significant predictors of ADIN, the technology-specific factors are also critical to predict ADIN. For example, ANTH and ETHC

Table 6: Global urban AI initiatives and influencing factors

City name	AI Initiative	Adoption influencers	Sources
Toronto	SC initiative was launched in partnership with Google in 2017. The goal was to provide smart services using advanced technologies such as AI, cameras, and sensors. The project was abandoned due to constant concerns raised from citizens regarding data privacy, surveillance, and ethical use of data.	PSEC, ETHC, and TSTC	Artyushina, 2020
Helsinki	AI-enabled chatbot launched for 24x7 automated delivery of parking permits. Efforts were taken for local language support, involving citizen groups, informing citizens about data privacy and security, and ensuring ethical implementation.	PEXP, MLOP, ANTH, PSEC, ETHC, and TSTC	Mark and Anya, 2019
Dubai	Projected as the hub for emerging technology-led urban administration. AI is being implemented for various service automation, ensuring the right governance process.	PEXP, EEXP, FCND, PSEC, and ETHC	Batayneh *et al.*, 2021
Singapore	This city-state nation has created the Model AI Governance Framework for how AI systems should operate and also raise public knowledge and foster trust in technology.	PEXP, EEXP, PSEC, TSTC, and ETHC	Falco *et al.*, 2021
Melbourne	For Melbourne, technology is not deployed for the sake of it but used only when it provides value and experience to residents. It aims to predict traffic patterns hours in advance and set the stage for linked and driverless cars. Australian citizens are debating about data, trust, and AI ethics as the digital transformation progresses.	PEXP, EEXP, PSEC, and ETHC	Yigitcanlar *et al.*, 2021

factors should be studied when automated systems are being considered for public-facing applications. MLOP remains a significant factor for studies involving multilingual communities. Moreover, PSEC and TSTC should be considered when studying novel technology adoption.

CONCLUSION

AI's role in smart city services

Governments around the world are evaluating cutting-edge technologies to ease urban difficulties. Specifically, AI is being trialed for a variety of pressing needs in the delivery of citizen services. With its text, audio, and image processing capabilities, AI technology will be able to automate numerous smart city services. Currently, due to poor information management, a lack of strategic data usage, and operations undertaken in siloed groups, numerous government services experience delays, inefficiency, and public displeasure in a large and diverse country like India. Increased public dissatisfaction with current service delivery systems is also attributed to their reliance on physical paper and human intervention at every stage. Moreover, the deployment of continuous monitoring systems generating a huge volume of data in a smart city could make the municipal administration more technically and logistically challenging, exposing government services to increasingly intricate and unforeseen obstacles. AI will ensure automated, continuous monitoring of services and also can help in forecasting the service availability based on the external environment and data sources. For example, with AI, smart city authorities will be able to address the expanding and more diverse needs of citizens without needing to engage additional personnel. Secondly, the AI4SC system will reduce or eliminate the need for human night-shift personnel, thereby reducing the cost of providing government services. Thirdly, citizens can submit service requests to AI4SC at any time, from any location, and track their progress through fulfillment. Importantly, ordinary citizens with limited computer skills and resources will profit from its human-like characteristics, which will allow them to utilize the service in a shorter period of time. In the era of Generative AI where the models (such as ChatGPT, Bard, Midjourney, StableDiffusion etc.) capable of generating human-like text, audio, and image data, it is very important that citizens trust e-governance information delivered by AI agents and alleviate those concerns. AI-powered chatbots and virtual assistants can handle citizen inquiries and automate routine tasks. Data analytics and AI-driven decision-making can provide insights for urban planning and resource allocation. AI can optimize smart city infrastructure, such as transportation and energy systems. Predictive maintenance can be implemented to identify maintenance needs and reduce disruptions. AI can enhance public safety through surveillance and anomaly detection. Citizen engagement and feedback can be facilitated through AI-driven platforms.

Factors influencing AI's adoption intention

With India being a multilingual country, the study recommends applications to support various languages for higher adoption. Overall, to make AI safe for citizen services, it is important to establish an ethical framework, prioritize data privacy and security, ensure transparency and explainability of AI systems, mitigate biases, maintain human oversight and accountability, continuously monitor and evaluate AI systems, educate citizens about AI, and foster collaboration and regulation. These measures will help in safeguarding citizen data, addressing biases, promoting transparency, and ensuring responsible and trustworthy AI deployment. By following these steps, municipalities can enhance the safety of AI in citizen services while upholding ethical principles and protecting individual rights. Based on the current state of e-governance in an Indian urban city and the potential of AI in e-governance, the purpose of this research was to investigate the factors influencing the adoption intention of AI in the delivery of citizen services within a smart city in India. Studying adoption intention prior to the actual usage of novel technologies and designing products and services according to numerous aspects that influence adoption intention increases the likelihood that the technology will be utilized successfully in the future. The study identifies enablers and barriers to adoption using UTAUT as the base theory. The research study provides policy recommendations for governments and service providers regarding the usage of AI technology in the public sector. More specifically, the study highlights the significance of ethics, fairness, accountability, and transparency when implementing AI for citizen services, which in turn affects trust in the systems that are critical for the government's Digital India initiative. India being a diverse country of various cultures and demographics, the ethical aspects will play a key role in adoption of AI-based services. In addition, in order to be fair to data owners, the data gathering strategy for services should require explicit consent. These considerations would ultimately assist in increasing the return on technology investment drawn from tax payments from citizens. Smart city administrators can leverage AI in several areas to enhance e-governance. It will enable citizens to acquire relevant and accurate answers to their commonly asked questions without significant technological expertise. However, this research study also revealed that the smart city management must make sufficient effort to ensure that AI4SC service delivery is equitable for all socioeconomic levels of city residents. In addition, in order to be fair to data owners, the data gathering strategy for services should require explicit consent. Furthermore, municipal authorities should ensure enough accountability throughout the whole AI4SC system design, development, and deployment process. The significance of transparency and explainability of AI in achieving general social acceptability is highlighted as well, which would be helpful for smart city administrators. Additionally, the proposed AI system should be as secure as any existing online system, with a low likelihood of manipulation and privacy intrusion. In summary, AI would assist smart cities by increasing productivity and service efficiency.

Directions for future research

This study has a few limitations and the directions for future research. First, it was conducted in the western region of the Indian state of Maharashtra. Careful thought is required before generalizing the research's conclusions to different geographic regions. Second, this research was limited to smart city services in urban settings. Future researchers may investigate the application of AI for smart village services in rural locations. Third, this study only measured adoption intention. In future, the scholars can investigate actual usage post implementation. Furthermore, there is a scope for further exploration into more specific AI applications, like 24x7 surveillance and healthcare diagnostics. Administrators and citizens in Indian smart cities will gain a great deal from the outcomes of such experiments, which will assist them in developing more effective procedures and systems for providing citizen services.

AUTHOR CONTRIBUTIONS

S. Kuberkar performed the literature review, experimental design, analyzed and interpreted the data, prepared the manuscript text, and manuscript edition. S. Singh helped in the literature review and manuscript preparation. T. Singhal helped in the literature review, experimental design, and manuscript preparation.

ACKNOWLEDGEMENT

The authors would like to acknowledge the anonymous citizen respondents who responded to the survey. The study was not funded by any national or private agency.

CONFLICT OF INTEREST

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

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PUBLISHER'S NOTE

Tehran Urban Research and Planning Center (TURPC) Publisher remains neutral with regard to jurisdictional claims in published maps and institutional afflictions.

ABBREVIATIONS

%	Percent
β	Regression Coefficient
ADIN	Adoption Intention
AI4SC	Artificial Intelligence for Smart Cities
AMOS	Analysis of Moment Structures
ANTH	Anthropomorphism
ASV	Average Shared Variance
AVE	Average Variance Explained
CFA	Confirmatory Factor Analysis
CR	Composite Reliability
EEXP	Effort Expectancy
ETHC	Ethical Concerns
FCND	Facilitating Conditions
Fig.	Figure
H (1, 2,10)	Alternate Hypothesis
ICT	Information and Communication Technology
MLOP	Multilingual Option
MSV	Maximum Shared Variance
NITI	National Institution for Transforming India
p-value	Probability value
PBEN	Perceived Benefits
PCA	Principal Component Analysis
PEXP	Performance Expectancy
PSEC	Privacy and Security Concerns
SEM	Structural Equation Modeling
R^2	Coefficient of determination
SINF	Social Influence
SPSS	Statistical Package for the Social Sciences
TSTC	Trust Concerns
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor

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HOW TO CITE THIS ARTICLE

Kubeka, S.; A.; Singh, Sh.; Singhal, T.K., (2024). Adoption intention of artificial intelligence enabled smart city services from citizens' perspective. Int. J. Hum. Capital Urban Manage., 9(1): 29-46.

DOI: 10.22034/IJHCUM.2024.01.03

URL: https://www.ijhcum.net/article_708421.html