Smart Cities and AI: Leveraging User Data for Big Data Analytics Insights*

Ruchika Pharswan[1,*,†], Rohit Goel[2,†], Kajal Kansal[3,†]

[1]Department of Information Technology : Delhi Technological University
[2]Department of Computer Science and Engineering : Maharaja Agrasen Institute of Technology
[3]Department of Computer Science and Engineering : Maharaja Agrasen Institute of Technology

Abstract

Artificial intelligence (AI) has gotten progressively significant in everyday life, from navigation systems to intelligent assistance, prompting initiatives like Smart City. Thus, the successful adoption of the smart city is directly or indirectly linked to the acceptance of advancedtechnologies. Researchers have mainly explored the technological framework of smart cityadoption. However, the impact of the emerging technologies and their acceptance on smart city adoption yet largely unexplored and continues to be an abstract idea on various grounds, which leaves a gap. This paper aims to determine the influencing factors of smart city adoption by analyzing the AI application user's experience and acceptance from the lens of various stakeholders. In this paper, we have extracted the data from the Social Media Platform, then performed sentiment analysis and network analysis to identify the significant constructs that can impact the Smart cities adoption. Then we use stepwise regression analysis with permutation testing approach via SVM classifier to determine the influence of constructs on the user in AI application experience. The study establishes that perceived innovation, value, compatibility, easeof use, enthusiasm, performance, efficiency, social influence, and user expertise significantly increase the stakeholder's AI experience. The current study can be an excellent source for variousstakeholders' reference while adopting AI or comparative Technology deployed in the smart city.

Keywords

Artificial Intelligence, Smart Cities, Support Vector Machine, Social Media Platform

1. Introduction

The prominence of smart cities emanates from the changes and challenges that emerge due to the growing urban population. The rapid rates of urbanization and the fast-growing population in urban areas present many concerns like a strain on existing infrastructure, traffic congestion, environmental changes, security issues, inefficacious medical facilities, and outmoded Technology and governance wherein smart cities intended to contribute and sustain a high quality of life [1]. The smart city is amalgamating advanced technologies to overcome modern problems to develop a more sustainable, substantial, and compelling city. However, the impact of these emerging technologies on smart city adoption is yet largely unexplored and continues to be an abstract idea on various grounds. Significantly, the smart cities ideas and development were inextricably associated with the emergence of new information technologies. So, it becomes imperative to pay attention to the factor directly and indirectly associated with the usage and

SCCTT-2024: International Symposium on Smart Cities, Challenges, Technologies and Trends, 29th Nov 2024, Delhi, India
* Corresponding author.
† These authors contributed equally.
ruchikapharswan2024@gmail.com (R. Pharswan); rohitgoyal8178@gmail.com (R. Goel); kansalkajal.30@gmail.com (K. Kansal)
0000-0003-0478-8168 (R. Pharswan)

applications of those technologies that can impact smart city services[2].

Though numerous researchers have examined the possible smart city enablers such as technological frameworks and evaluate their impacts on the adoption process, the linkage betweentechnology adoption and smart city development is yet to be explored[3]. To bridge this knowledge gap, the current study aims to understand the impacts of user's experience of AI applications on smart city developments to accelerate its acceptance and adoption.

Although new technology, infrastructure, and industries can build smart cities, its adoption is more likely to depend upon technology stakeholder's participation and experience Smart city's idea can be implemented and adopted extensively only when users have familiarity and prior experience with the constituent technologies[4]. Consequently, there is an essential missing link or insufficiently addressed issue: how thestakeholder's AI application experience may be critical to the smart cities' adoption[5]. There needs to be a study that identifies and connects all the determinants of the stakeholder's AI applications experience associated with the smart cities. Our research will be essential to bridge this literature gap and be a leader for future research[6]–[8].

This study's primary objective is to focus on the information system (IS) context of smart cities from various stakeholder lenses. The undertaken research addresses the following research questions aiming to identify the linkage between AI adoption, stakeholder's AI experience, and smart cities adoption:

RQ*: How is stakeholder's AI application experience associated with the successful adoption in thesmart city?*

This paper has proposed a robust framework that collects data from social media platforms (SMP)(i.e., Twitter) based on hashtags and keywords related to the AI application and smart cities, followed by preprocessing and training the data. We have used social media analytics-based sentiment analysis. After that, we performed network analysis. The second phase is the validationphase. Stepwise regression and support vector machines are used to confirm the significance of identified constructs that can impact the user's AI application experiences and, consequently, smartcity adoption.

The rest of the paper is organized as follows: We consolidated available literature related to smart city adoption in the second section. The third section portrays the research methodology followed for the undertaken research. The fourth section outlines the findings along with the hypothesis development that is validated in a later section. The fifth section discourses the implications of our results. Simultaneously, the sixth section has concluded our research's learnings, followed by limitations and future research scopes in the seventh section.

2. Literature Review

Many investigations investigate the association between innovation reception and the elements that impact it. In any case, there is restricted exploration looking at the connection between taking on arising advances, like computerized reasoning, and the improvement of savvy urban areas. This leaves a hole in the ongoing writing. Our review expects to address this hole through our proposed research.

2.1 AI and Technology adoption

AI is considered an essential component of digital transformation and is globally viewed as one of the core competitive technologies by organizations in every sector. AI's proven potential is extremely capable of developing efficient and smart cities. Despite the propelling advantages of AI, evidence indicates that AI's adoption is still in the nascent stage[9], [10]. There is a need for a study that uncovers the factors influencing AI adoption. Numerous works of literature discuss IT adoption, focusing more on organizations' points of view. The old theories discussed some characteristics like the complexity of Technology,compatibility, the relative advantage to use it, observability, and last one is trialability. They considered these factors are essential for the diffusion of any technology. Various studies exploreAI in multiple domains. Some studies consider the theoretical aspect of AI and other deal with AIadoption in different sectors. Many studies have explored AI's pervasive nature, and not much literature exploring the AI adoption from the stakeholder's lens leaves a gap. Studies on AI adoption from technical, organizational, and environmental aspects are available so far[11]. Therefore,there is a need for research that identifies the factors influencing AI adoption from various stakeholders' viewpoints, such as AI services provider, governance, AI end-users. Our study is intended to fill this gap with our proposed work.

2.2 Stakeholders Participation and Experience

Due to the pertinence of smart cities to various stakeholders, it is crucial to consider theopportunities and barriers associated with its adoption from the stakeholders' lens.

2.2.1 AI Application Providers

The experience of AI vendors with these technologies also impacts AIadoption. Adopting any new technology, among others, is also influenced by the marketing strategies of the vendors, so for the overall adoption of AI, it is crucialto consider the factors that influence the vendor's AI experience. Since not everyone is very versed with new technologies, it requires a certain level of skills to use the technologies like AI, so vendor's expertise is one can be one of the factors that can influence one's AI usage experience and hence the opinion regarding its adoption Studies validate the significant impact technology vendors have on technology adoption, directly or indirectly associated with the vendor's AI experience.

2.2.2 Government

Administrating a smart city government must become smart and incorporate technology-based decision systems for better planning and policymaking. The smart Government envisions improving the governing strategies, procedures and modifying the community services to provide the best. The Government's readiness to promote the new Technology will encourage growth and adoption[12]. Government targets accomplishing transparency inadministrative procedures, policies-making systems, governance systems, and decision-making systems to improve the planning and deployment of public services and accessible assets. These factors can be considered the factors influencing the Government AI experience and their AI acceptance and adoption decision.

2.2.3 Citizen

Residents are the smart services users; thus, it is pivotal to address the factors driving orhindering smart cities' adoption from the user's perspective to ensure the successful and substantialadoption of smart cities. The participation and engagement of citizens is a measure that impacts smart city adoption. Numerous research has effectively been conducted on citizen participation. If citizens find AI-based products and services easy to use, safe, and secure, they might like to continue with more technologies or solutions like smart cities[10]. There are notion of technology adoption from the user's viewpoint relies on their experience. Various research explored citizen participation, yet being an emerging technology, AI user experience is less explored. Citizen's AI experience relies upon factors like ease of use, security of their data, their prior experience or expertise, as discussed in some literature[13].

3. Methodology

The whole methodology is separated into two portions. The first is scrutinizing stage, where information encompassing AI and smart cities adoption is extracted from SMP. Different exploratory investigations such as sentiment analysis and network analysis are performed to recognize the potential constructs. The subsequent stage is the validation stage. Wherein factors influencing the AI user's experiences are again determined and validated, however, by statistical techniques.

3.1 Phase one: Scrutinizing phase

3.1.1 Research setting and data collection

Twitter is one of the largest SMPs in terms of both number of active users online and the scale ofreach and penetration to focused groups of users. Hence mining the data from Twitter helps us analyze the opinions and understand the signals that could lead to theoretical constructs that can be tested later. The data collection framework consists of four modules. Firstly, the data extraction module is built on the python toolkit utilizing the Twitter streaming API with the results stored in a .csv file[14]. The keywords and hashtags used for data collection are ["#ArtificialIntelligence,' "#AI,' "#Smartcity,'"#DataScience,' "#Citizens,' "#Applications,' "#Smartgrid,' "Sustainability,' "Automatic"]. We downloaded over one million tweets.

As part of the next step, we start preprocessing the data by cleaning, stemming, tokenization, and normalization. It also includes removing duplicate texts, denoising, and spell-checks. Normalizingthe data caters to interpreting the standard terms from slang jargon linguistics. Stemming overall normalizes all the tenses to present tense and tokenization, creating tokens to words with usage inthe sentences, i.e., noun, adjective, adverb. Data summarization is critical to reducing a large volume of unstructured text to manageable form while keeping the essential signal information athand.

3.1.2 Sentiment and communities of topics

We use sentiment scores to identify the polarity of the expressed opinion in each of the tweets. Wethen classify the tweets into positive, negative, and neutral sentiment groups and then repeat the procedure on extreme positive and negative sentiment groups to understand the prominent themes[13].Term frequency-inverse document frequency (TF-IDF) is a statistical method that tells the most important words in a sample of texts by reflecting how vital a topic is basis the frequency of the occurrence of the same in the entire sample.

3.2 Phase two: Validation phase

In the second phase, we again extracted the data from the SMP and performed preprocessing. Thenwe use the permutation testing approach to identify the significant constructs that impact the useris AI application experience, for which we use an SVM classifier. As a result of the permutation testing approach, we now have a set of significant factors, and now we validate the same by usingthe stepwise regression analysis

4. Finding

4.1 Insights from the Phase one analysis: Scrutinizing Phase

In this paper, data was analyzed from Twitter to provide insights into the conversation around smartcities and AI adoption. Figure 1 represents the general keywords that often appeared in the conversations. When we have closely analyzed the conversations, we learned that some leading experiential keywords illustrate the positive and negative discussions from the various stakeholders, as shown in figure 2.

Figure 1: Word cloud representing conversation around AI adoption and Smart cities

Figure 2: Word cloud representing positive and negative conversations group around AI adoption and Smart cities.

For instance, keywords like "efficient", "solution", "readiness", "governance", "technology", "confidence", "interaction" have been sighted from the positive conversations. Moreover, these keywords are outwardly related to the theoretical presumptions we have undertaken for the hypothesis development while theory building. Applying a similar approach to the negative conversations, we observe keywords like "fear," "e-attack," "failure," "privacy," "inconsistency," "emotions," "identity- theft" came into the picture. Furthermore, these keywords are also associated with the hypothetical theory we have constructed for AI adoption and smart cities.

4.2 Insights from Network analysis and clustering

In our study, words are the unit of analysis, and we have effectively sighted some keywords emerging from the conversations. However, it is imperative to determine how the extracted keywords are associated with each other as a part of a more extensiveconversation. To recognize this, we develop a network diagram of leading keywords for each sentiment group.

Figures 3 and 4 represent the network diagrams of positive and negativeconversations, respectively. Scrutinizing both network diagrams concurrently, we figured out thatalthough both the network diagrams are around smart cities and AI adoption, however, exhibit different perspectives. One network diagram entails more development, automation, governance,reliability, and success, whereas another reflects the severe concern to cost, privacy, complexity, latency, and security.

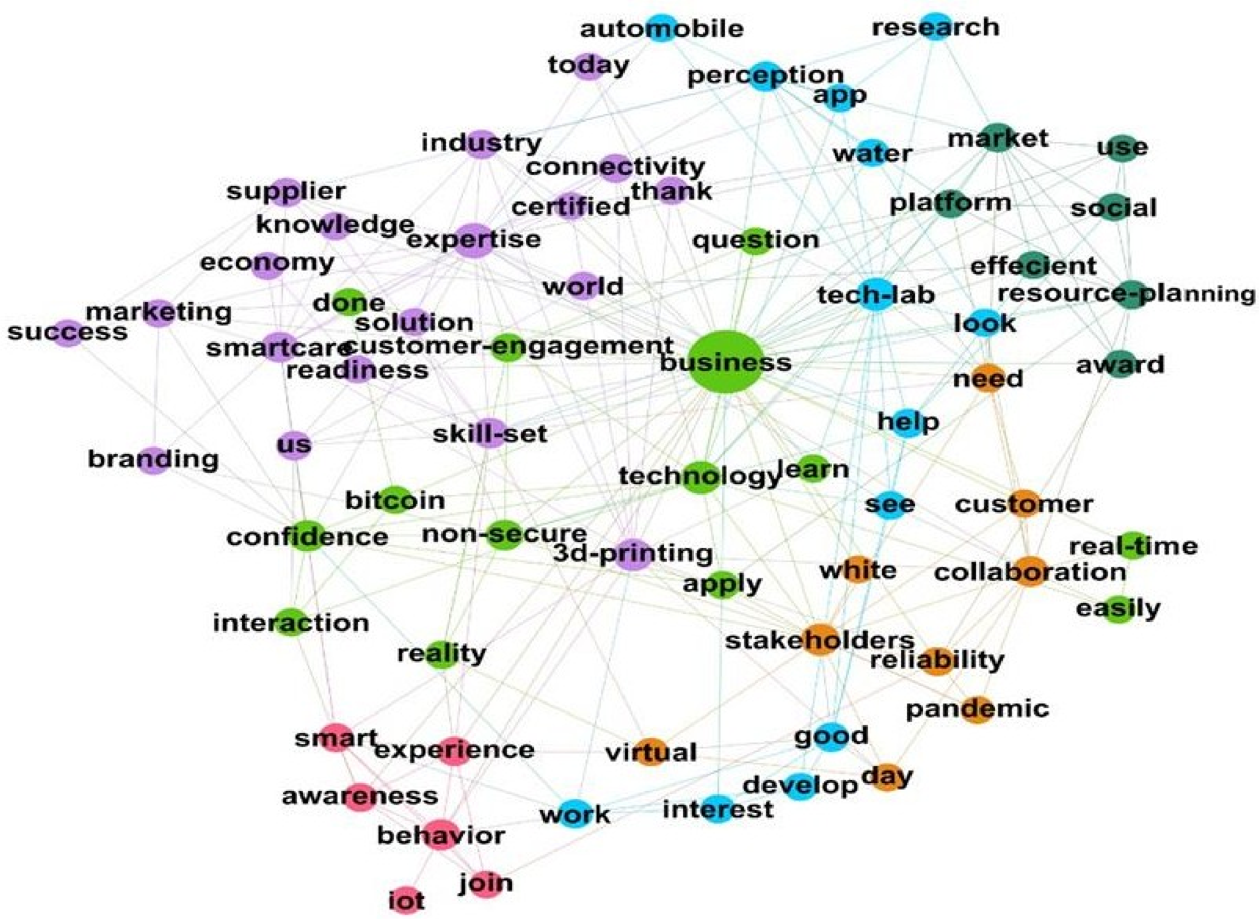

Figure 3: Network Diagram for positive group conversation

To obtain the most significant set of constructs, wehave used the permutation testing approach. In this technique, random labels are assigned to the constructs, and then we use an SVM classifier to train the model. After that, we test the significanceof each construct by using the "one left out "cross-validation strategy. We use this procedure in iteration until we separated the most significant constructs. Finally, the permutation testing approach is presented in box and whisker plot in figure 5. We can see that four constructs are discovered to be insignificant, having a p-value more prominent than 0.05.

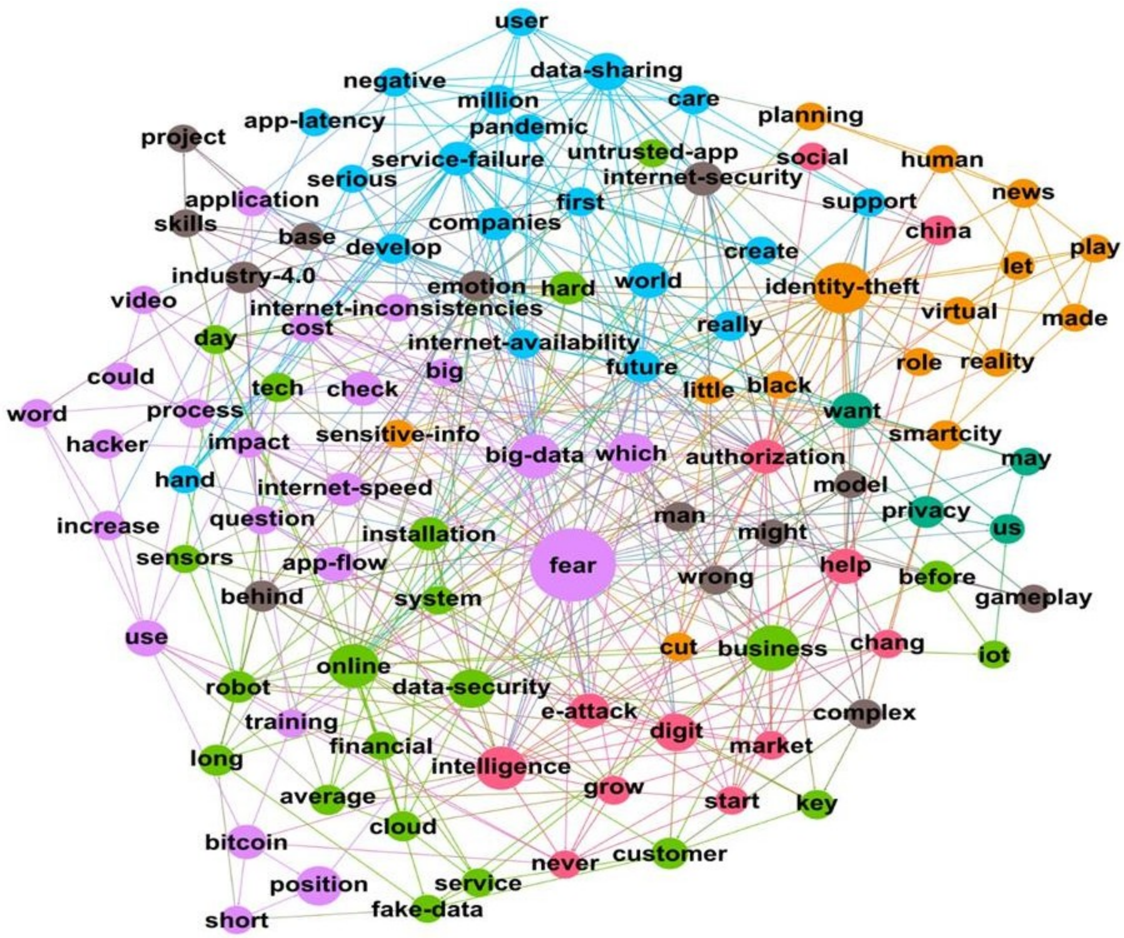

Figure 4: Network Diagram for Negative group conversation

We have identified fifteen constructs and tested each of these hypotheses individually using Pearson's chi-square to determine their P-values. Those who are having p-values less than or equivalent to 0.05 are considered as the most significant factors. However, the constructs AI expertise, perceived compatibility, perceived security, and perceived risk was not accepted due to its higher p-values. Out of 15 potential constructs identified from the literature and our Prior analysis, 11 contracts were eventually found to be significantly associated with the AI usage experience of various stakeholders. The result of regression analysis is represented in Table 1.

This examination analyzes the elements that drive or impede the reception of savvy urban communities, zeroing in on how artificial intelligence innovation and its applications are seen by different partners. Existing examinations on innovation reception feature that perspectives like execution, effectiveness, chances, trust, straightforwardness, client mastery, and individual mentalities assume key parts in whether new advancements are embraced.

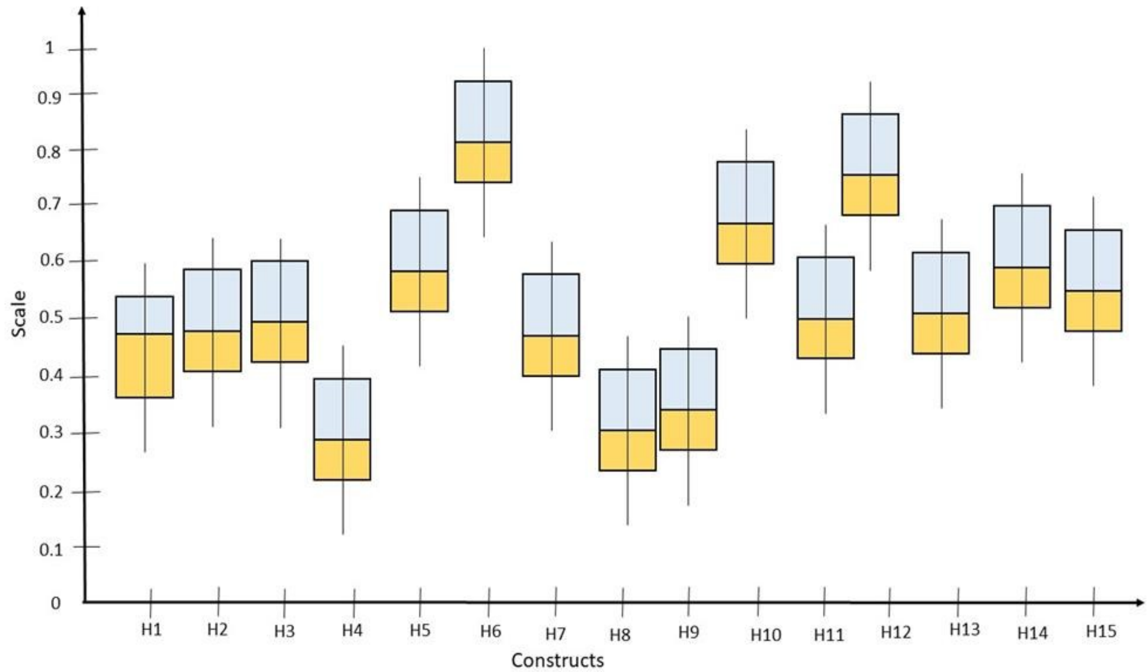

Figure 5: Construct's Significance testing using SVM

Be that as it may, there is restricted examination tending to brilliant city reception according to the viewpoints of various partners, especially as far as client experience. Since shrewd city drives are as yet advancing, many elements impacting their reception stay neglected. Strikingly, regions like computer based intelligence administration and straightforwardness have not been concentrated on in that frame of mind of shrewd city reception and clients' encounters with man-made intelligence applications. Our proposed work proposed structure spans these holes by applying bits of knowledge from the innovation reception model, conduct science, and administration science to investigate the connection between different variables and client encounters with computer based intelligence.

Looking at results we can say AI usage experience for vendors also relies on their creativity and innovative capabilities. If they are receptive to innovation and intend to engage with the new technologies, they will undoubtedly approach the technology acceptance. AI is the backbone technology for smart cities. If application providers perceive that AI applications are more beneficial than other technologies, they should positively impact their AI usage experience. However, some technologies apply to niches, which may not be compatible with many existing structures, minimizing users' anticipation and hence creates a dismissive attitude towards the Technology. Many pieces of literature identified inadequate technical expertise as a significant factor hindering the Technology's complete acceptance and evolution. The higher the security imparted by the Technology, the more the user tends to use it and have an affirmative experience. Lower the risk user perceive while using a new technology inculcates higher trust and confidence to accept it. Expanding the contention that perceived risk can contrarily affect the user intends to utilize the Technology. Trust is somewhere related to the risk arising from using the AI applications or solutions. It tends to be said that trust is linearly related to the user experience. Higher confidence naturally better the perception of users regarding AI and its applications. Social influence plays a massive role in improving the adoption rate, especially in online applications. Social groups can act as supporting groups helping in comforting and compelling the user to try new Technology.

Table 1: Result of stepwise regression

Index	Coef.	Std. Err.	t	P> |t|	[0.025	0.975]
Constant	0.3272	0.001	269.096	0	0.325	0.33
Perceived Value	0.1393	0.037	3.765	0	0.067	0.212
Perceived Innovation	0.1368	0.029	4.784	0	0.081	0.193
Perceived Readiness	1.444	0.141	-10.265	0	-1.72	-1.168
AI Expertise	0.0254	0.026	-0.961	0.331	-0.077	0.026
Efficiency	0.0248	0.022	-1.144	0.252	-0.067	0.018
Performance	0.1201	0.068	1.762	0.078	-0.013	0.254
User's literacy	0.3487	0.128	-2.731	0.006	-0.599	-0.098
Perceived Compatibility	- 0.0083	0.02	0.413	0.68	-0.031	0.048
Perceived Security	0.1847	0.26	-0.71	0.478	-0.694	0.325
Perceived Ease of Use	0.337	0.133	-2.535	0.011	-0.598	-0.076
Social Influence	2.0008	0.048	-41.432	0	-2.095	-1.906
User Expertise	1.4483	0.515	2.812	0.005	0.439	2.458
Perceived Risk	0.0039	0.03	0.131	0.896	-0.054	0.062
Perceived Enthusiasm	1.2314	0.162	7.596	0	0.914	1.549
Perceived Trust	0.1029	0.039	1.564	0.057	0.014	0.312
R-Square	56.2					
Adjusted R-Square	52.2					

5. Conclusion

The entire concept of the smart city is to make people, Government, and Technology smart. Emerging Technology like AI is the keystone of smart cities. Thus, to understand how users perceive smart city initiatives, it is imperative to identify how users perceive the AI applications, how positive their user experience with AI is, and the factors influencing the AI usage experience.The entire study is divided into two segments. First is scrutinizing phase where data surrounding AI and smart cities adoption is extracted from SMP and various exploratory analysis is performedto identify potential construct. The second phase is the validation phase. Wherein data constructs are again identified but by statistical techniques. As the finding of the first phase, we identified two groups having upbeat sentiments regarding AI and smart city adoption. We identified two network diagrams for each sentiment group. Mapping all the findings of phase one, we determined fifteen constructs that, according to the phase one analysis, influences the user's AI application experience. The second phase is the validation phase. We try to validate the step one findings by using statistical techniques. We use stepwise regression analysis along with the permutation testing techniques wherein SVM is used as a classifier. Multiple set of significant constructs has been made and tested using SVM and stepwise regression. Mapping the output of phase one and phasetwo, we find out of 15 constructs, 11 constructs were significant and influenced the AI and smartcity adoption. This will be the first study that identified the crucial factors for accelerating the user's AI application experience and hence smart cities adoption via the highlighted approaches inthis research.

6. References

[1] E. Araral, “Why do cities adopt smart technologies? Contingency theory and evidence from the United States,” *Cities*, vol. 106, no. July, p. 102873, 2020, doi: 10.1016/j.cities.2020.102873.

[2] T. Fontes, V. Costa, M. C. Ferreira, L. Shengxiao, P. Zhao, and T. G. Dias, “Mobile payments adoption in public transport,” *Transp. Res. Procedia*, vol. 24, pp. 410–417, 2017, doi: 10.1016/j.trpro.2017.05.093.

[3] P. Zhao, Y. Yen, E. Bailey, and M. T. Sohail, “Analysis of urban drivable and walkable street networks of the ASEAN smart cities network,” *ISPRS Int. J. Geo-Information*, vol. 8, no. 10, 2019, doi: 10.3390/ijgi8100459.

[4] N. Staletić, A. Labus, Z. Bogdanović, M. Despotović-Zrakić, and B. Radenković, “Citizens’ readiness to crowdsource smart city services: A developing country perspective,” *Cities*, vol. 107, no. July, p. 102883, 2020, doi: 10.1016/j.cities.2020.102883.

[5] Y. Lim, J. Edelenbos, and A. Gianoli, “Identifying the results of smart city development: Findings from systematic literature review,” *Cities*, vol. 95, no. October 2018, p. 102397, 2019, doi: 10.1016/j.cities.2019.102397.

[6] M. Zhang, P. Zhao, and S. Qiao, “Smartness-induced transport inequality: Privacy concern, lacking knowledge of smartphone use and unequal access to transport information,” *Transp. Policy*, vol. 99, no. January, pp. 175–185, 2020, doi: 10.1016/j.tranpol.2020.08.016.

[7] R. K. R. Kummitha and N. Crutzen, “How do we understand smart cities? An evolutionary perspective,” *Cities*, vol. 67, no. May, pp. 43–52, 2017, doi: 10.1016/j.cities.2017.04.010.

[8] Q. Liu, Z. An, Y. Liu, W. Ying, and P. Zhao, “Smartphone-based services, perceived accessibility, and transport inequity during the COVID-19 pandemic: A cross-lagged panel study,” *Transp. Res. Part D Transp. Environ.*, vol. 97, no. June, p. 102941, 2021, doi: 10.1016/j.trd.2021.102941.

[9] A. Shamsuzzoha, J. Niemi, S. Piya, and K. Rutledge, “Smart city for sustainable environment: A comparison of participatory strategies from Helsinki, Singapore and London,” *Cities*, vol. 114, no. March, p. 103194, 2021, doi: 10.1016/j.cities.2021.103194.

[10] S. EL HILALI and A. AZOUGAGH, “A netnographic research on citizen’s perception of a future smart city,” *Cities*, vol. 115, no. March, p. 103233, 2021, doi: 10.1016/j.cities.2021.103233.

[11] H. Jiang, “Smart urban governance in the ‘smart’ era: Why is it urgently needed?,” *Cities*, vol. 111, no. June 2020, p. 103004, 2021, doi: 10.1016/j.cities.2020.103004.

[12] G. Masik, I. Sagań, and J. W. Scott, “Smart City strategies and new urban development policies in the Polish context,” *Cities*, vol. 108, no. June 2019, p. 102970, 2021, doi: 10.1016/j.cities.2020.102970.

[13] P. Monachesi, “Shaping an alternative smart city discourse through Twitter: Amsterdam and the role of creative migrants,” *Cities*, vol. 100, no. March, p. 102664, 2020, doi: 10.1016/j.cities.2020.102664.

[14] P. Neirotti, A. De Marco, A. C. Cagliano, G. Mangano, and F. Scorrano, “Current trends in smart city initiatives: Some stylised facts,” *Cities*, vol. 38, pp. 25–36, 2014, doi: 10.1016/j.cities.2013.12.010.

[15] S. A. Bagloee, M. Heshmati, H. Dia, H. Ghaderi, C. Pettit, and M. Asadi, “Blockchain: The operating system of smart cities,” *Cities*, vol. 112, no. May 2019, p. 103104, 2021, doi: 10.1016/j.cities.2021.103104.