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Effects of Smart City on Utilizing Customer Data to Enhancing Customer Delight: A Practical Study

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ABSTRACT

One of the main interests for institutions these days is how to use information technologies and communication systems to find and share data to enhance both corporate business and governmental services' efficiency and effectiveness. This study analyzed the impact of smart cities as an independent latent factor on several factors related to customer data, namely Customer Data Collection, Customer Data Analysis, Customer Data Mining, Customer Data Warehousing, and Customer Digital Solutions, which served as dependent latent factors. It also examined the impact of each of these factors as independent variables on the Customer Delight factor. The study based on a sample of 413 customers residing in smart cities to derive its results and concluded that all relationships were statistically significant. Specifically, Customer Data Mining, Customer Data Warehousing, and Customer Data Collection positively impacted Customer Delight, with path values of 0.334, 0.229, and 0.139, respectively. In contrast, Customer Data Analysis and Customer Digital Solutions had a negative impact on Customer Delight, with impact coefficients of -0.191 and -0.049, respectively. The study also concluded that the smart cities factor positively influenced all latent factors, except for Customer Data Mining, which was inversely related to the smart cities factor, with an impact coefficient of -0.066.

1. INTRODUCTION

The concept of smart cities has evolved significantly during the 21st century, becoming one of the most important ideas in urban development (Gracias et al., 2023). The significance of smart cities has increased alongside expectations of the growing trend toward urbanization, which is projected to reach 50% of the world's population by 2050 (Singh et al., 2022). As smart cities continue to develop at a steady pace, it is essential to study them to understand their effects on various factors, including Customer Digital Solutions, Customer Data Collection, Customer Data Analysis, Customer Data Warehousing, and Customer Data Mining. This study aims to explore these effects and analyze the impact of Customer Digital Solutions on the Customer Delight factor within the context of smart cities and their advancements.

1.1. The study gap

There have been many recent studies and research addressing smart cities through analysis; however, few have examined their impact on the combination of factors considered in the current study "together". This is particularly important given the lack of clarity surrounding this relationship, which must be established as an initial concept. This understanding forms a theoretical basis for improving or modifying certain factors that appear to be closely related to the smart cities component. Ultimately, this will maximize the benefits derived from these cities, leading to enhanced data related to customers residing in them (Amponsah, 2024; Zahra, 2024). In addition, the scarcity of empirical studies directly addressing the impact of digital solutions in smart cities on customers and their satisfaction represents the most significant gap for this study. Most previous research has focused on general customer satisfaction or service efficiency, leaving a void in understanding the nuances of customer satisfaction associated with smart cities and their accompanying technologies. Conversely, many studies have examined either smart city technologies or customer experience separately, but few have integrated both aspects to analyze their combined impact on customer satisfaction. This has created a need for research that connects digital solutions to enhanced customer experiences in smart urban environments.

1.2. The research questions

Smart cities are a new concept, which justifies the need to research and study them from various perspectives. To demonstrate the impact of these cities on factors related to customers, the current study attempts to answer the following research questions:
- Does smart city positively impact offering digital solutions for customers?
- Does smart city positively impact customer data collection?
- Does smart city positively impact customer data analysis?
- Does smart city positively impact customer data storage?
- Does smart city positively impact customer data extraction?
- Does digital solutions for customers positively impact customer satisfaction?
- Does smart city in general influence customer delight?

2. WHAT SMART CITY CONCEPT MEANS?

The term "smart cities" refers to cities that utilize technology, artificial intelligence tools, and digital solutions to enhance customer experience and provide more efficient methods for managing resources and services (Alshurideh, 2024; Lee et al., 2024). This is achieved by creating a comprehensive customer database that relies on digital infrastructure to ensure integration and connectivity (Ozturk, 2024; Sukkari, 2024). Gracias et al. (2023) noted that there is no universally agreed-upon definition of a smart city. This lack of a clear definition can pose challenges for policymakers, city planners, and stakeholders seeking to develop and implement smart city initiatives. However, through their research into structured literature, they found that the primary focus of smart city definitions revolves around improving the quality of life for residents. A smart city employs a combination of data collection, processing, and dissemination technologies, alongside networking and computing technologies, as well as cybersecurity measures and privacy protections (Akour et al., 2024; AlHamad et al., 2024). This approach encourages innovative applications aimed at enhancing the overall quality of life for its citizens (Ghazal et al., 2021; El Khatib et al., 2023). These dimensions include utilities, health, transportation, entertainment, and government services (Caragliu et al., 2011). Additionally, Singh et al. (2022) demonstrated that a smart and sustainable city is an innovative city that utilizes information and communication technologies (ICTs) and other means to enhance the quality of life, improve the efficiency of urban operations and services, and increase competitiveness. This approach ensures that the needs of both present and future generations are met in terms of economic, social, and environmental aspects.

3. LITERATURE REVIEW

3.1. Customer digital solution

The need for smart cities to rely on advanced technology and digital solutions for collecting, mining, analyzing, and storing customer data stems from the massive volume of this data and the necessity of providing solutions that facilitate customers' lives, enhance their satisfaction levels, and increase the speed of service delivery (Alzoubi & Inairat, 2020; Al Kurdi et al., 2025). These technologies have been adopted in many cities around the world (Allam & Newman, 2018). Hong Kong is considered one of the leading smart cities that has leveraged digital solutions to provide government services to citizens through the creation of the "IAM" Smart platform. This platform enables citizens to access public services seamlessly and perform most government transactions, such as paying bills or renewing documents, thereby increasing transaction speed and saving time and effort. It also allows them to access their personal data through the platform itself, ensuring data protection and simplifying customer interactions with the government (Mohanty et al., 2016). Also, on the medical services side, for example, the use of telemedicine technology has been explored in Hong Kong, making healthcare more accessible and allowing citizens to receive medical consultations online without the need to visit hospitals or clinics. Additionally, Internet of Things (IoT) technology is being utilized to control pests in public areas (Allam & Newman, 2018; Anaam et al., 2023). These smart systems help maintain the cleanliness of the city and reduce the spread of diseases. To analyze the relationship between smart cities and customer digital solutions, the following hypothesis can be formulated:

H1: Smart city influence positively customer digital solutions.
H2: Customer digital solutions influence positively customer delight.

3.2. Customer data collection

Customer data collection is closely linked to the possibilities offered by the Internet of Things (IoT) for gathering customer data through various technologies that have significantly enhanced the efficiency and effectiveness of this process (Bojanowska, 2019; Antouz et al., 2023). Although the methods used to collect data about customers may differ, the fundamental process of data collection does not vary much based on the specialization or purpose of the data being collected (Kabir, 2016). With the increasing role of technology and the IoT, consumer data has become a crucial tool for shaping business strategies, to the extent that it is now used to transform some companies based on understanding consumer perceptions, which is achieved by collecting their data, particularly regarding their consumer behavior (Lia, 2015). In the context of smart cities that rely on technology and business digitization, it is essential to demonstrate the impact these cities have on the process of collecting consumer data. To achieve this, the following hypothesis has been formulated:

H3: Smart city influence positively customer data collection.
H4: Customer data collection influence positively customer delight.

3.3. Customer data analysis

Technological progress and the digitization of economic life have been accompanied by numerous applications and tools used in data analysis, especially with the development of artificial intelligence tools that encompass a wide range of capabilities, such as spreadsheets, visual analysis, query programs, data extraction programs, data storage programs, and decision support systems (Lia, 2015). All of these advancements have enabled companies to analyze customer satisfaction with the services and products they provide, with the aim of continuously improving these offerings (Grljević & Bošnjak, 2018). Given the close connection between smart cities and the overall digitization of life, due to the advanced technology and ease of access to modern technological tools, it is essential to examine the effects of these cities on the process of analyzing consumer data. This relationship can be expressed through the following hypothesis:

H5: Smart city influence positively customer data analysis.
H6: Customer data analysis influence positively customer delight.

3.4. Customer data warehousing

Data warehouses are essential tools used in customer relationship management analysis to determine the impact of these relationships on marketing decisions, which in turn also influence the design of data (Cunningham & Chen, 2006). Their importance stems from the need to store data and information efficiently and retrieve it easily when required, which is a crucial determinant of the effectiveness of using this data, especially in light of the advancements provided by artificial intelligence tools and the digitization of life (Gallo et al., 2010). In addition, data warehouses contain various datasets, the most significant of which include operational data, decision support data, and external data relevant to the organization's business units. The quality of data warehouse design plays a vital role in facilitating the analysis of the data they contain and enabling quick access to this information (Khan et al., 2012). Since smart cities are built on technological development, the relationship between these cities and data warehouses should be evident from the perspective of customers residing in these environments. To analyze this relationship, the following hypothesis has been formulated:

H7: Smart city influence positively customer data warehousing.
H8: Customer data warehousing influence positively customer delight.

3.5. Customer data mining

Data mining intersects with database management systems and the field of data partitioning that has emerged in the information and communication age (Das & Nayak, 2022). It is also considered an overlapping process with data warehouse design, as both processes facilitate quick access to important data that enables customer market analysis, helping to identify the optimal combination of offerings that align with customer preferences and (Berry et al., 2004). Smart cities provide numerous modern technological techniques that facilitate the process of data mining for the purpose of collection and analysis. Accordingly, to understand the extent of the impact of smart cities on data mining, the following hypothesis has been formulated:

H9: Smart city influence positively customer data mining.
H10: Customer data mining influence positively customer delight.

3.6. Customer delight

Customer happiness is the primary goal of any business or company, evidenced by the substantial amount of money that organizations invest to achieve it (Alshurideh et al., 2023). Happiness and satisfaction are two synonyms terms used mainly to present customer positive feedback or good experience or reaction of buying (Alhammadi & Alshurideh, 2023). Also, customer satisfaction is a fundamental condition for marketing and selling products and services, ultimately leading to significant revenues and improved business performance (Parasuraman et al., 2021). Interest in customer satisfaction dates back a long time and has been a research focus for over 20 years due to its (Barnes & Krallman, 2019). Given that smart cities are designed to be integrated, it is essential to study their effects on customer delight. Therefore, the following hypothesis has been formulated:

H11: Smart cities influence positively customer delight.

3.7. Research model

The relationship between the study variables can be expressed through the following model:

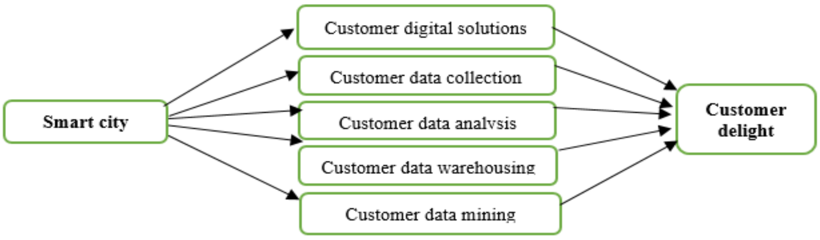

Figure 1. Study model.

Figure (1) illustrates the relationship between the independent latent factor (Smart Cities) and each of the dependent factors. It also shows how all the latent factors function as independent factors in relation to the dependent factor (Customer Delight).

4. METHODOLOGY AND DATA ANALYSIS

The study aimed to analyze the relationship between smart cities as an independent factor and several dependent factors related to the digital development of customer data. It relied on a sample size of 413 individuals who are customers residing in smart cities. The variables were measured using a questionnaire consisting of several dimensions corresponding to the seven factors under study, with internal variables saturated and measured through the statements that formed the questionnaire as a whole. The questionnaire underwent validity and reliability tests, and then the SMART PLS program was adopted to test the study hypotheses based on the outputs of the structural equation modeling.

4.1. Convergent validity

The validity of the model was analyzed based on several metrics: factor loadings, which should preferably be higher than 0.65; composite reliability (CR), which should ideally exceed 0.7; and average variance extracted (AVE), which should also be greater than 0.5. Additionally, the variance inflation factor (VIF) should preferably be lower than 10. These metrics are essential for ensuring that the constructs in the model are reliable and valid, thus supporting the robustness of the study's findings. The following table (1) shows the results of the validity of the proposed model:

Tale 1. Reliability and Validity

Indicators	VIF	Loadings	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
SC1	1.06	-0.11	0.776	0.922	0.875	0.651
SC2	4.612	0.915				
SC3	3.94	0.912				
SC4	4.6	0.933				
SC5	2.125	0.838				
CDS1	1.399	0.799	0.864	0.966	0.817	0.539
CDS2	1.626	0.903				
CDS3	1.255	0.444				
CDS4	1.068	-0.04				
CDS5	1.03	0.205				
CDC1	2.426	0.849	0.888	0.731	0.895	0.636
CDC2	3.189	0.905				
CDC3	2.119	0.838				
CDC4	1.983	0.584				
CDC5	2.307	0.773				
CDA1	1.055	0.153	0.704	0.806	0.756	0.548
CDA2	1.361	0.303				
CDA3	1.685	0.802				
CDA4	2.011	0.896				
CDA5	2.311	0.794				
CDW1	1.61	0.551	0.836	0.958	0.866	0.57
CDW2	2.171	0.82				
CDW3	1.607	0.699				
CDW4	1.792	0.768				
CDW5	1.785	0.892				
CDM1	3.3	0.906	0.777	0.745	0.866	0.54
CDM2	4.643	0.906				
CDM3	2.679	0.762				

CDM4	2.323	-0.112				
CDM5	2.28	-0.121				
CD1	3.573	0.154				
CD2	4.585	0.307				
CD3	2.778	0.543	0.878	0.831	0.766	0.538
CD4	2.004	0.937				
CD5	2.013	0.632				

Table (1) shows that the loading rates of each variable on its latent factor ranged from large to medium and small values, including both positive and negative loading rates. In general, the loading rates of the variables linked to the latent factor "Smart City" were high, with three of them exceeding 0.91, one at 0.838, while the only low loading rate for this factor was -0.11, associated with the variable SC1, which refers to "reliable and high-speed internet infrastructure". Also, the factor "Customer Data Collection" also demonstrated a high loading rate, with the loading rate value of the variable CDC2, "storage and use of their personal data," reaching 0.905. Additionally, two other values exceeded 0.83, and one reached 0.773. However, the lowest value was for the variable "preferences regarding the use of their personal information," which stood at 0.584. Further, as for the remaining factors, the loading rates for their internal variables varied heterogeneously between low and medium rates. Regarding the values of the Variance Inflation Factor (VIF), all values were within acceptable limits, as none exceeded 4.643. Notably, the upper acceptable limit is 10, indicating that the proposed model does not suffer from multicollinearity. Moreover, looking at the values of the Average Variance Extracted (AVE), all were higher than the acceptable threshold of 0.5. Additionally, the values of the questionnaire evaluation indicators—Cronbach's alpha, Composite Reliability (rho_a), and Composite Reliability (rho_c)—were above the acceptable lower limits. Therefore, we can assess the quality of the questionnaire used for data collection on one hand and the quality of the proposed model on the other.

4.2. Discriminant validity

The average variance extracted (√AVE) is one of the most important indicators for testing discriminant validity, as the value of this indicator should be greater than the squared correlation estimate. Discriminant validity tests assess the lack of correlation between the constructs that make up the structural model, thereby evaluating the degree to which one construct is distinct from the others. Discriminant validity is achieved when the average variance extracted (AVE) is greater than the squared correlation (Hair et al., 2012). The following table (2) shows the results of the discriminant validity test of the proposed model using the Fornell-Larcker Criterion:

Table 2. Discriminant Validity

Factors	Customer data analysis	Customer data mining	Customer data warehousing	Customer delight	Customer digital solution	Smart Cities	Customer data collection
Customer data analysis	0.694						
Customer data mining	0.144	0.558					
Customer data warehousing	0.729	0.011	0.772				
Customer delight	0.103	0.310	0.174	0.819			
Customer digital solution	0.122	-0.065	0.229	-0.012	0.579		
Smart Cities	0.182	-0.066	0.180	-0.047	0.709	0.807	
Customer data collection	0.245	-0.023	0.152	0.125	0.104	0.120	0.818

Through the correlation values between the study dimensions representing its latent factors ha are represented in previous table (2), it was observed that the values did not exceed large levels, nor were they non-existent or small. This indicates that the correlation value between the highest latent factors and the lowest root value of the Average Variance Extracted (√AVE) is higher, suggesting that the discriminant validity of the proposed model is considered good. Specifically, the square root of each structure is greater than its highest correlation with any other structure**.**

4.3. Testing inner model

The internal model test relies on analyzing the correlation values between each dependent factor and its associated independent factors through the structural equation model based on the Partial Least Squares (PLS) method. The following figure (2) illustrates the results of this test:

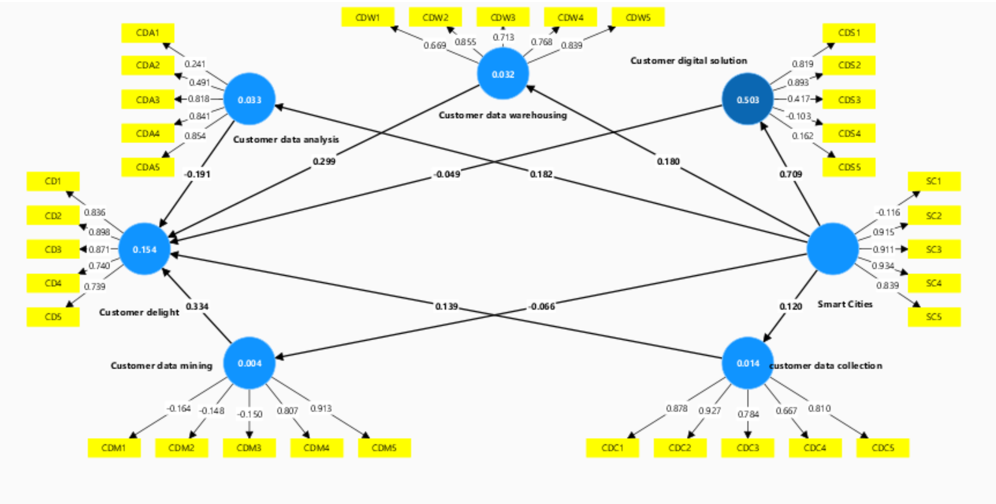

Figure 2. Structured Model

Based on the previous figure (2), showing the values of the coefficient of determination, which is one of the most important indicators of the model's explanatory power, this coefficient indicates the percentage of variance explained in the dependent factor (smart cities) through the variance in the independent factors. According to the figure, the independent factor that had the largest impact on the variance of the smart cities factor is Customer Digital Solution, explaining 49.5% of the variance in the smart cities factor. In contrast, the contributions of the other independent factors to the variance of smart cities were relatively low:

- Customer Data Warehousing: 4.5%
- Customer Data Analysis: 5%
- Customer Delight: 3.5%
- Customer Data Mining: 1.3%
- Customer Data Collection: 2.3%

Thus, the factors "Customer Data Mining" and "Customer Data Collection" had the least impact, with coefficients of determination of 1.3% and 2.3%, respectively.

4.4. Goodness of Fit and Hypotheses Testing

The analysis of the explanatory power of the model was based on several indicators, the most important of which is the coefficient of determination (R-square). This value ranges between 0 and 1, where the explanatory power—representing the amount of variance that can be explained in the dependent variable based on the independent variables—increases as the R-square value approaches (Lucky Bamidele Benjamin et al., 2024).Hereinafter, the able (3) shows he outputs of goodness of model and path coefficients between all factors:

Table 3. Hypothesis Results

Relations	Path coefficients	R-square	t-value	p-value
Customer data analysis -> Customer delight	-0.191	0.145	6.531	0.011
Customer data mining -> Customer delight	0.334		8.011	0.005
Customer data warehousing -> Customer delight	0.299		13.294	0
Customer digital solution -> Customer delight	-0.049		9.256	0.003
Customer data collection -> Customer delight	0.139		9.004	0.005
Smart Cities -> Customer data analysis	0.182	0.033	5.635	0.025
Smart Cities -> Customer data mining	-0.066	0.004	5.524	0.033
Smart Cities -> Customer data warehousing	0.18	0.032	7.821	0.009
Smart Cities -> Customer digital solution	0.709	0.503	7.109	0.009
Smart Cities -> Customer data collection	0.12	0.014	5.14	0.034

Table (3) displays the path coefficients (regression coefficients) between each of the independent and dependent factors according to the study hypotheses. It also presents the calculated significance levels (P-values) corresponding to the T-student test, all of which were less than the theoretical significance level of 0.05. This indicates support for the study hypotheses. Consequently, the effect between each independent factor and the dependent factor is considered significant and statistically relevant, with variations in the direction of the relationships. Specifically, three relationships exhibited negative values for the path coefficients, indicating an inverse relationship between the corresponding factors. In contrast, the remaining relationships were directly proportional, as evidenced by the positive values of the path coefficients. Additionally, table (3) shows the values of the coefficients of determination, which indicate the extent of variance in the four factors that can be explained by the variance in the independent factors.

5. DISSCUSION OF RESULTS AND IMPLICATIONS

The experimental study analyzed the relationship between smart cities (SC) as an independent latent factor and the dependent latent factors: Customer Digital Solutions (CDS), Customer Data Collection (CDC), Customer Data Analysis (CDA), Customer Data Warehousing (CDW), and Customer Data Mining (CDM). The results indicated that the relationships between these factors were substantial and statistically significant, as demonstrated through significance tests based on P-values. However, not all correlations were direct. Specifically, both CDA and CDS had an inverse effect on Customer Delight (CD), with impact coefficients of -0.191 for CDA and -0.049 for CDS. Additionally, the smart cities factor (SC) also exhibited an inverse effect on Customer Data Mining (CDM), with an impact coefficient of -0.066. In contrast, the relationship between the smart cities factor (SC) and Customer Digital Solutions (CDS) demonstrated the highest degree of correlation, with a positive impact coefficient of 0.709. This was followed by the effect of Customer Data Mining (CDM) on Customer Delight (CD), which had a positive impact coefficient of 0.334. To clarify more, the results obtained can be interpreted as follows: A change of one unit in each of the following factors will cause an average change in Customer Delight (CD) by the respective coefficients:

- Customer Data Analysis (CDA): -0.191
- Customer Data Mining (CDM): 0.334
- Customer Data Warehousing (CDW): 0.299
- Customer Digital Solution (CDS): -0.049
- Customer Data Collection (CDC): 0.139-

Additionally, a change of one unit in the Smart Cities factor (SC) will cause an average change in Customer Data Analysis (CDA) by 0.182 in the same direction, an opposite change of -0.066 in Customer Data Mining (CDM), and changes in the same direction of 0.18, 0.709, and 0.12 in Customer Data Warehousing (CDW), Customer Digital Solution (CDS), and Customer Data Collection (CDC), respectively. Further, the factors Customer Data Analysis, Customer Data Mining, Customer Data Warehousing, Customer Digital Solution, and Customer Data Collection explain 0.145 of the variance in the Customer Delight factor, as indicated by the coefficient of determination value. The Smart Cities factor explains 0.33 of the variance in Customer Data Analysis, 0.004 in Customer Data Mining, 0.032 in Customer Data Warehousing, and 0.014 in Customer Data Collection. Moreover, the largest proportion of variance that the Smart Cities factor contributes to explaining is in the Customer Digital Solution factor, where the proposed model can explain 0.503 of the variance in Customer Digital Solution through the variance in the Smart Cities factor. Regarding the internal variations, the internal variables exhibited variation in the saturation values across their latent factors.

- Smart cities factor

For the Smart Cities factor, the four variables (SC2 to SC5) showed high correlation values, exceeding 90% for the first three variables and reaching 83.9% for variable SC5.

- Customer data solution factor

In the Customer Data Solution (CDS) factor, the most saturated variable was Digital Solutions Available Across Multiple Devices (CDS2), with a saturation value of 0.893. Following closely was the variable Easily Accessible and User-Friendly for Residents of All Ages (CDS1), with a saturation value of 0.819. In contrast, the least saturated variable was Minimal Downtime or Technical Issues (CDS4), which had a negative saturation value of -0.103.

- Customer data collection factor

The Customer Data Collection (CDC) factor demonstrated a high degree of saturation among its variables, with all five variables exhibiting positive saturation values ranging from 0.667 to 0.927.

- Customer data analysis factor

Conversely, the Customer Data Analysis (CDA) factor was less homogeneous regarding the saturation of its internal variables. The lowest saturation value was 0.241 for the variable Meaningful Insights that Inform the Development and Improvement of Public Services (CDA1), while the highest saturation was for the variable Ongoing Relevance and Effectiveness of the Insights Generated (CDA5), which had a saturation value of 0.854. The Customer Data Warehousing (CDW) factor also exhibited high saturation values for its internal variables. The least saturated variable was Structured and Easily Accessible Repository (CDW1), with a saturation value of 0.669. The remaining variables showed high saturation values, with the highest being for Ability to Maintain the Integrity and Security of Their Personal Information (CDW2), which had a saturation value of 0.855. In contrast, the Customer Data Mining (CDM) factor displayed a significant prevalence of negative saturations among its variables. Three out of the five variables were saturated with negative values:

- Leading to a Deeper Understanding of Resident Needs, Preferences, and Behaviors (CDM1): -0.164.
- Positive Impact on the Quality and Responsiveness of the Digital Solutions (CDM2): -0.148.
- Anticipate and Address the Evolving Needs and Challenges of Its Residents (CDM3): -0.150.

The importance of this study arises from the significance of smart city methods, which are regarded as crucial concepts and entities worldwide and have recently emerged as a prominent idea. Therefore, it can be said that the study's value lies in providing a theoretical framework on smart cities. Also, this study analyzes the factors influenced by smart cities, particularly those related to technological concepts and customer service. Additionally, the study includes a review of the practical framework and previous research addressing smart cities, serving as a foundational starting point for researchers who may later explore this topic through further study and analysis.

7. CONCLUSION, LIMITATIONS AND FUTURE STUDIES

Smart cities are crucial due to their significant impact on customer data and the associated processes, particularly in data collection, data mining, data warehousing, and digital solutions. These factors play a vital role in achieving customer delight within smart cities, as their unique structure can enhance all processes related to customer data. However, smart cities are not without their challenges; certain factors have been negatively associated with them. This indicates an opportunity to improve the role of these cities in analyzing customer relationships and data. By enhancing the design of data warehousing and digital solutions, smart cities can better leverage customer data to foster stronger relationships and improve overall customer satisfaction. Regarding the study limitation, it is important to clarify tha the scarcity of previous studies addressing the subject of this research is considered one of the most significant constraints influencing the study. Additionally, the difficulty in reaching clients to fill out the questionnaires was another major constraint that hindered the implementation of the study. Time constraints also played a role, causing delays in completing the research due to the need to redistribute several questionnaires multiple times. This was often a result of logical errors in the responses or instances of incomplete answers.to add more regarding the study recommendation, the researcher recommends exploring ways to address the effects of smart cities on factors related to sustainability and sustainable development, the green economy, and a clean environment. Additionally, it is essential to highlight the role of these cities in enhancing creativity and innovation, particularly in the Arab world.

REFERENCES

Akour, I., Nuseir, M. T., Al Kurdi, B., Alzoubi, H. M., Alshurideh, M. T., & AlHamad, A. Q. M. (2024). Intelligent Traffic Congestion Control System in Smart City. In Cyber Security Impact on Digitalization and Business Intelligence: Big Cyber Security for Information Management: Opportunities and Challenges (pp. 223-234). Cham: Springer International Publishing.

Al Kurdi, B. H., Alshurideh, M. T., & Alzoubi, H. M. (2025). Determinants of Employee Happiness and Their Impact on Customer Happiness: Empirical Evidence from the UAE Banking Industry. Jordan Journal of Business Administration, 21(2), 173-193.

AlHamad, A. Q. M., Hamadneh, S., Nuseir, M. T., Alshurideh, M. T., Alzoubi, H. M., & Al Kurdi, B. (2024). Robot-based security management system for smart cities using machine learning techniques. In Cyber Security Impact on Digitalization and Business Intelligence: Big Cyber Security for Information Management: Opportunities and Challenges (pp. 169-180). Cham: Springer International Publishing.

Alhammadi, S. M. K., & Alshurideh, M. T. (2023). Factors affecting customers' happiness: a systematic review in the service industries. In International Conference on Advanced Intelligent Systems and Informatics (pp. 510-526). Springer, Cham.

Allam, Z., & Newman, P. (2018). Redefining the smart city: Culture, metabolism and governance. Smart Cities, 1(1), 4–25.

Alshurideh, M. (2024). Utilize internet of things (IOTs) on customer relationship marketing (crm): An empirical study. International Journal of Management and Marketing Intelligence, 1(1), 11-19.

Alshurideh, M. T., Al Kurdi, B., Alzoubi, H. M., Akour, I., Obeidat, Z. M., & Hamadneh, S. (2023). Factors affecting employee social relations and happiness: SM-PLUS approach. Journal of Open Innovation: Technology, Market, and Complexity, 9(2), 1-10.

Alzoubi, H. M., & Inairat, M. (2020). Do perceived service value, quality, price fairness and service recovery shape customer satisfaction and delight? A practical study in the service telecommunication context. Uncertain supply chain management, 8(3), 579-588.

Amponsah, C. (2024). The Effects of Pros and Cons of Applying Big Data Analytics to Enhance Consumers' Responses. International Journal of Management and Marketing Intelligence, 1(3), 1-8.

Anaam, E., Hasan, M. K., Ghazal, T. M., Haw, S. C., Alzoubi, H. M., & Alshurideh, M. T. (2023, February). How private blockchain technology secure iot data record. In 2023 IEEE 2nd International Conference on AI in Cybersecurity (ICAIC) (pp. 1-6). IEEE.

Antouz, Y. A., Akour, I. A., Alshurideh, M. T., Alzoubi, H. M., & Alquqa, E. K. (2023, March). The impact of internet of things (IoT) and logistics activities on digital operations. In 2023 International Conference on Business Analytics for Technology and Security (ICBATS) (pp. 1-5). IEEE.

Barnes, D. C., & Krallman, A. (2019). Customer Delight: A Review and Agenda for Research. Journal of Marketing Theory and Practice, 27(2), 174–195. https://doi.org/10.1080/10696679.2019.1577686

Berry, M. J., Linoff, G. S., & Marketing, F. (2004). Customer Relationship Management Second Edition Data Mining Techniques.

Bojanowska, A. (2019). Customer data collection with Internet of Things. MATEC Web of Conferences, 252, 03002. https://doi.org/10.1051/matecconf/201925203002

Caragliu, A., Del Bo, C., & Nijkamp, P. (2011). Smart cities in Europe. Journal of urban technology, 18(2), 65-82.

Cunningham, C., & Chen, P. P. (2006). Data Warehouse Design to Support Customer Relationship Management Analyses. Journal of Database Management, 17(2), 62-84.

Das, S., & Nayak, J. (2022). Customer Segmentation via Data Mining Techniques: State-of-the-Art Review. Smart Innovation, Systems and Technologies, 281, 489–507. https://doi.org/10.1007/978-981-16-9447-9_38

El Khatib, M., Ahmed, G., Alshurideh, M., & Al-Nakeeb, A. (2023). Interdependencies and integration of smart buildings and smart cities: a case of Dubai. In The effect of information technology on business and marketing intelligence systems (pp. 1637-1656). Cham: Springer International Publishing.

Gallo, C., De Bonis, M., & Perilli, M. (2010). Data warehouse design and management: theory and practice. IEEE Members. Dipartimento di Scienze Economiche, Matematiche e Statistiche Università Di Foggia Largo Papa Giovanni Paolo II, 1-17.

Ghazal, T. M., Hasan, M. K., Alshurideh, M. T., Alzoubi, H. M., Ahmad, M., Akbar, S. S., ... & Akour, I. A. (2021). IoT for smart cities: Machine learning approaches in smart healthcare—A review. Future Internet, 13(8), 218.

Gracias, J. S., Parnell, G. S., Specking, E., Pohl, E. A., & Buchanan, R. (2023). Smart Cities—A Structured Literature Review. In Smart Cities, 6(4), 1719–1743. Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/smartcities6040080

Grljević, O., & Bošnjak, Z. (2018). Sentiment analysis of customer data. Strategic Management-International Journal of Strategic Management and Decision Support Systems in Strategic Management, 23(3), 38-49.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. Journal of the Academy of Marketing Science, 40(3), 414–433.

Khan, A., Ehsan, N., Mirza, E., & Sarwar, S. Z. (2012). Integration between Customer Relationship Management (CRM) and Data Warehousing. Procedia Technology, 1, 239–249. https://doi.org/10.1016/j.protcy.2012.02.050

Lee, K. L., Teong, C. X., Alzoubi, H. M., Alshurideh, M. T., Khatib, M. E., & Al-Gharaibeh, S. M. (2024). Digital supply chain transformation: The role of smart technologies on operational performance in manufacturing industry. International Journal of Engineering Business Management, 16, 1-19.

Lia, M. (2015). Customer Data Analysis Model using Business Intelligence Tools in Telecommunication Companies. In Database Systems Journal, VI (2), 39-62. http://www.statsoft.com/

Lucky Bamidele Benjamin, Prisca Amajuoyi, & Kudirat Bukola Adeusi. (2024). Marketing, communication, banking, and Fintech: personalization in Fintech marketing, enhancing customer communication for financial inclusion. International Journal of Management & Entrepreneurship Research, 6(5), 1687–1701. https://doi.org/10.51594/ijmer.v6i5.1142

Mohanty, S. P., Choppali, U., & Kougianos, E. (2016). Everything you wanted to know about smart cities. IEEE Consumer Electronics Magazine, 5(3), 60–70. https://doi.org/10.1109/MCE.2016.2556879

Kabir, S. M. S. (2016). Methods of data collection. Basic guidelines for research: An introductory approach for all disciplines, 1(9), 201-275. https://www.researchgate.net/publication/325846997

Ozturk, I. (2024). Factors influencing the use of the Internet of Things (IoT) to enhance customer relations and customer experience. International Journal of Management and Marketing Intelligence, 1(2), 1-9.

Parasuraman, A., Ball, J., Aksoy, L., Keiningham, T. L., & Zaki, M. (2021). More than a feeling? Toward a theory of customer delight. Journal of Service Management, 32(1), 1–26. https://doi.org/10.1108/JOSM-03-2019-0094

Singh, D. K., Sobti, R., Jain, A., Malik, P. K., & Le, D. N. (2022). LoRa based intelligent soil and weather condition monitoring with internet of things for precision agriculture in smart cities. IET Communications, 16(5), 604–618.

Sukkari, L. (2024). The impact of big data analytics on customers' online buying. International Journal of Management and Marketing Intelligence, 1(2), 10-19.

Zahra, A. (2024). Using intelligent information systems to enhance customers’ knowledge. International Journal of Management and Marketing Intelligence, 1(3), 9-16.