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Smart Decision-Making in the Future City: A Social Innovation Perspective

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ABSTRACT

The evolution of future cities represents a crucial dimension of global sustainable urbanization. Although an increasing amount of study has investigated diverse aspects of future city development, relatively insufficient focus has been placed on analyzing the phenomenon from the perspective of smart decision-making. In this setting, artificial intelligence (AI) acts as a transformational technology force capable of redefining decision-making processes and advancing urban sustainability. This study examines the influence of AI in strengthening smart decision-making and its potential to foster sustainability in future city environments, viewed through the framework of social innovation. A thorough research model was developed to clarify the complex interrelationships among AI, social innovation, and smart decision-making via triple correlations. Within this framework, social innovation acts as a mediating variable, whereas the internal threats linked to the Internet of Things (IoT) operate as a moderating factor. Demographic factors, including gender, age, and education, were incorporated as control variables. An empirical survey was administered to capture citizens' views on the contribution of AI to decision-making processes within city governance. Employing purposive sampling ensured the collection of data that was both relevant and representative. Data analysis was performed using SPSS and AMOS, with confirmatory factor analysis (CFA) applied to assess the validity and reliability of the measurement constructs. The empirical findings reveal that AI—particularly through the usage of big data derived from sensor networks—plays a central role in facilitating social innovation and data-based decision-making in future urban contexts. The results further demonstrate that social innovation mediates the relationship between AI and decision-making effectiveness, thereby strengthening governance efficiency. Conversely, internal IoT vulnerabilities were found to weaken this positive association, highlighting the need for robust cybersecurity measures. Overall, this study provides significant theoretical and practical implications for policymakers, urban planners, and scholars. It underscores the pivotal role of social innovation in integrating AI into the design of sustainable and resilient cities, while simultaneously emphasizing the importance of addressing security and governance challenges stemming from IoT-related risks. By illuminating these dynamics, the research contributes to the broader discourse on AI-enabled urban sustainability and smart governance in the era of digital transformation.

Keywords: Future city, Sustainability, Social innovation, Artificial intelligence, Smart decision-making.

INTRODUCTION

Scholars have increasingly contended that artificial intelligence (AI) possesses transformative potential across multiple domains such as smart city development, governance, innovation management, and the enhancement of human capacities (Mikalef, 2021; Collins, 2021). Thus, the implications of AI for governance structures, decision-making processes, innovation ecosystems, and broader societal transformation have emerged as central themes in contemporary academic discourse and policy deliberation (Duan, 2019; Allam & Dhunny, 2019). Accelerated technological advancements have positioned AI as an indispensable element of modern life (Raisch & Krakowski, 2020) , while the proliferation of big data has further amplified its functional value by enabling more efficient resource allocation and evidence-informed decision-making (Salari, 2022). Within this context, AI acts as a catalyst for reconfiguring data generation and analytical practices in both public and private sectors, thereby fostering a deeper comprehension of complex social and environmental systems (Noordt & Misuraca, 2020; Arruda & H. Madhavji, 2017). Importantly, the integration of AI into smart city governance exemplifies a paradigmatic shift toward "smart" decision-making—an approach grounded in systematic data collection and analytical reasoning rather than reliance on intuition, simple evidence, or trial-and-error practices (Berntzen, 2018).

Researchers in smart city development have extensively examined and acknowledged the pivotal role of AI in facilitating smart and data-driven urban decision-making (Ahad, 2020; Thakker, 2020). However, emerging evidence suggests that multiple interrelated factors may directly or indirectly influence the decision-making dynamics in future urban environments. Recent studies, for instance, indicate that information and communication technologies (ICTs) alone do not fully account for the complexity of smart decision-making processes (Lytras, 2021). Municipal authorities, therefore, must also consider the importance of inclusive governance by engaging citizens and other key stakeholders in participatory decision-making. Deakin and Al Waer (2011) advanced this viewpoint by demonstrating how digital urban frameworks can integrate planning, decision-making, and design rules into comprehensive e-governance systems. Similarly, Diakaki (2010) proposed strategies to enhance the energy efficiency of future cities, emphasizing that effective urban management requires an integrated approach that balances energy, environmental, social, and economic dimensions. This study seeks to investigate the impact of AI, alongside social innovation and internal vulnerabilities inside the IoT, on decision-making processes in smart cities.

THEORETICAL BACKGROUND

A future city begins with a fundamental question: how can urban development advance sustainability and improve global well-being? It is widely acknowledged that AI and the concept of future smart cities are inherently intertwined (Dash & Sharma, 2022). A "future city" refers to an urban ecosystem that leverages ICT to enhance governance systems, stimulate economic growth, and improve citizens' quality of life. Such cities integrate smart systems across various sectors, including smart traffic management (Nastjuk, 2022), smart information management (Ma, 2019), and smart healthcare services (Lien & Cao, 2014). The growing smartness of cities is largely driven by the application of AI to analyze and interpret the vast datasets generated through urban operations and maintenance. By optimizing data processing—through advanced collection, cleaning, and storage—AI enables deeper analytical insights and evidence-based policy formulation (Rahmani, 2021). Moreover, AI facilitates administrative efficiency by supporting data-driven, adaptive decision-making processes that minimize human error and address common issues like inaccurate forecasting in public administration (Duan, 2019). Thus, the integration of AI and smart city development represents a pivotal shift in urban governance and societal progress, establishing these technologies as essential facilitators of sustainable and smart urban futures.

The concept of social innovation has increasingly attracted academic and policy attention, particularly within the social sciences (Satalkina & Steiner, 2022). Although widely invoked, the term encompasses diverse methodological interpretations and disciplinary adaptations, making its boundaries inherently fluid and interdisciplinary. Scholars argue that social innovation reconfigures the traditional dynamics among citizens, the state, civil society, and the market (Kim, 2021). Instead of depending on hierarchical, top-down governance, it promotes collaborative partnerships that allow citizens to engage more directly with government institutions, supplementing or even assuming roles historically fulfilled by the state (de Jong, 2019). In this context, citizens engage as active co-creators and "embedded urban resources," cooperating with public authorities to design and implement innovative solutions (Ardill & Lemes de Oliveira, 2018, p. 218–219). This participatory process contributes to making democracy and governance more horizontal, inclusive, and adaptive (Castro-Arce & Vanclay, 2019, p. 2259). Furthermore, public–private partnerships serve as a vital mechanism within this framework, particularly in the provision of public services (Jensen, 2016). The satisfaction of stakeholder interests, the alteration of socio-political structures, and the empowerment of involved participants represent three core dimensions of social innovation (Kim, 2021). Ultimately, while social innovation represents the potential for transformation, it is fundamentally oriented toward collective change (Millard & Fucci, 2023). In this regard, ICTs hold substantial potential to reshape conventional modes of communication and decision-making, thereby reinforcing collaborative governance.

Research Gaps and Conceptual Model

Although prior studies have demonstrated that AI can positively influence smart decision-making in future cities, a comprehensive understanding of the specific applications of AI in this area remains limited. This constraint largely arises from diverse contextual factors and cross-economic inconsistencies. For instance, Lopes (2017) examined the integration of AI as a potential replacement for human agents in smart decision-making processes. Nevertheless, as Vrabie and Tirziu (2016) emphasised, decision-making in smart cities extends beyond the realm of ICTs or technological capabilities; it is also impacted by the perspectives, assessments, and participatory inputs of city managers, citizens, and other stakeholders. Building on this, Jarrahi (2018) underscored the complementary interplay between human cognition and AI, advocating for a more pragmatic and proactive collaboration in managing complex, unpredictable, and ambiguous organisational environments. Similarly, Diakaki (2010) proposed strategic approaches to enhance the energy efficiency of smart cities, stressing the necessity for decision-makers to account for environmental, social, and financial considerations alongside technological aspects. Furthermore, Gibson and Roelvink (2012) introduced a social innovation framework that highlights the inclusion of marginalised social groups and their active participation in collective decision-making processes, thereby broadening the socio-political dimensions of smart governance. AI has been widely acknowledged in prior studies as a critical enabler of smart decision-making processes. Nonetheless, this study contends that additional underlying mechanisms mediate the relationship between these two constructs, drawing upon the empirical evidence and theoretical reasoning presented above. Specifically, a notable conceptual gap persists in the absence of a foundational theoretical framework that clarifies how AI facilitates smart decision-making through the mediating role of social innovation. This suggests that the linkage between AI and smart decision-making is not direct but rather operates indirectly via social innovation. To address this theoretical gap, the author explores an idea of third-variable effects, seeking to elucidate the mechanism by which an independent variable (IV) influences a dependent variable (DV) under the mediational hypothesis. According to MacKinnon (2000), mediation analysis divides the causal relationship between the IV and DV into two distinct components. The initial path represents the direct effect, whereby AI directly affects smart decision-making. The second path denotes the indirect effect, in which AI impacts the mediator—social innovation—which subsequently affects smart decision-making. The existence of this indirect pathway implies that AI shapes the conditions for social innovation, which in turn enhances the quality and efficacy of smart decision-making (D. MacKinnon, 2001).

Moreover, from a research standpoint, relatively few studies have simultaneously examined these four constructs within the context of future cities. By incorporating both mediating and moderating variables, this study extends the analytical framework beyond a simple bivariate examination, thereby providing a more thorough and realistic understanding of the phenomena under investigation. Such variables are essential when exploring complex correlational or causal relationships, as mediators explain the mechanisms through which two variables are connected, while moderators affect the strength and direction of that association.

Accordingly, this study seeks to advance the understanding of the role and value of social innovation in influencing the interaction between AI and smart decision-making within smart governance systems for future cities. Beyond its theoretical contribution, the research develops and empirically tests a moderated mediation model that clarifies both the direct and indirect relationships between AI utilization and smart decision-making. Specifically, the model contends that social innovation acts as a mediating mechanism, while internal IoT threats work as a moderating factor affecting these relationships. The proposed conceptual framework is illustrated in Figure 1.

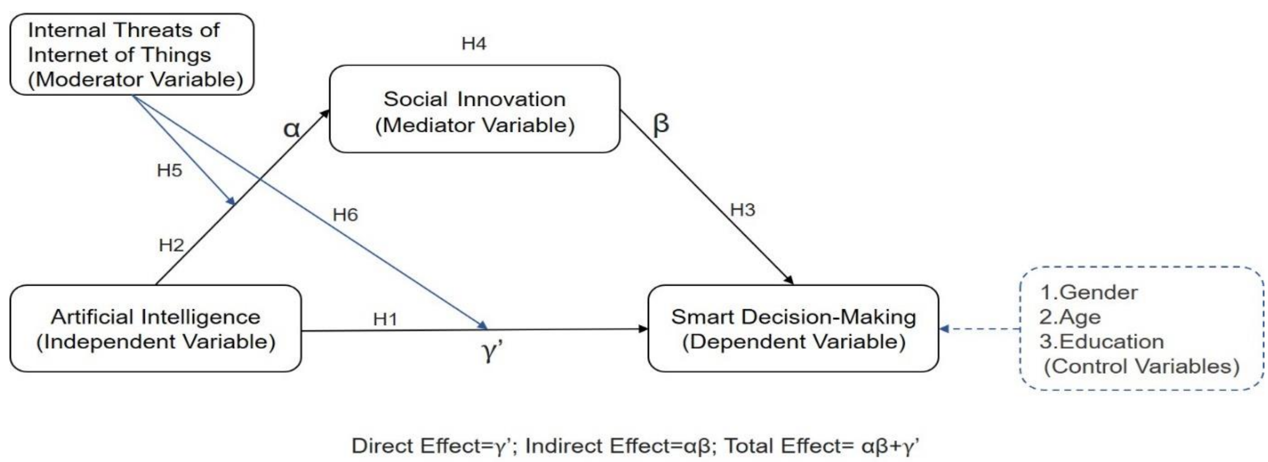

Figure 1. The Path Diagrams of the Conceptual Model.

Figure 1 depicts the structural pathways of a model that integrates both a mediating and a moderating mechanism. In this framework, the independent variable—AI—is proposed to impact an intermediary construct, social innovation (mediator), which in turn influences the final outcome, smart decision-making. Conceptually, this mediation framework describes a sequential causal process in which each variable influences the subsequent variables along the causal chain.

Hypothesis

The concept of the "smart city" has evolved considerably in response to the swift progress and widespread integration of digital technologies (Allahar, 2020). Contemporary understandings no longer regard smart cities as mere incremental digitization of public service provision. Instead, as Mora (2020) posits, future cities are envisioned as dynamic environments where digital technologies and data-driven systems are strategically leveraged to enhance economic development, increase quality of life, and advance sustainability goals. In this sense, the emerging paradigm redefines metropolitan areas as smart decision-making cities—integrated ecosystems that employ data intelligence to fully inform governance and policy processes.

AI and Smart Decision-Making

As the modern concept of "smartness" gains prominence, cities worldwide are progressively embracing digital transformation by incorporating sensors, data analytics, and advanced communication networks (Shahid, 2022). AI has become a pivotal component in urban governance, facilitating decision-making processes and forming the foundation for planning support systems (Peng, 2023). Nevertheless, in the realm of smart city planning, the development of practical tools that clearly demonstrate AI's potential to enhance existing frameworks remains limited (Bokhari & Myeong, 2022). Despite the examination of AI's significance in planning and expert systems many years ago (Alvarez, 2017), numerous early innovations in this domain ultimately faltered, mostly due to their functions being regarded as excessively simplistic (Dash & Sharma, 2022).

The development of future smart cities represents a complex, systemic, and highly integrated effort (Sharif & Pokharel, 2022). Previous studies have highlighted the significant potential of AI in analyzing and interpreting vast datasets to enhance decision-making processes within smart city ecosystems (Vinuesa, 2020). The expansion of smart cities is further driven by the collection and analysis of real-time data, which provides deeper insights into how urban environments adapt to and tackle their specific contextual difficulties (Li, 2022). Accordingly, the following hypothesis is proposed:

H_1: Employing big data within AI yields a positive impact on smart decision-making in future cities.

Triple correlations within AI, Social Innovation, and Smart Decision-Making

AI possesses considerable potential to revolutionize the ways in which public and private sectors interact with governments in policy formulation and decision-making processes. Scholl and Alawadhi (2016) highlight the significance of AI-enabled governance in fostering intercity collaboration to jointly develop smart public services that exceed the capacity of any single municipality. Likewise, the integration of big data analytics and advancements in machine learning enhance our understanding of how high-frequency, real-time urban systems operate (Jarrahi, 2018). However, within the realm of public administration—particularly at the municipal tier—the implementation of AI remains at an early stage (Mikalef, 2019). Decision-making supported by AI in these contexts is influenced by multiple determinants and constrained by an array of legal, political, policy-related, and contextual complexities (Dwivedi, 2021). Despite an expanding amount of research on AI, empirical and technical research focusing on AI adoption in public sector organisations is still limited (Collins, 2021). Consequently, the transformative capacity of AI to enhance smart and evidence-based decision-making is frequently undermined by challenges associated with social engagement, organisational structures, technological constraints, and regulatory or policy barriers.

The recognition of social innovation as a pivotal component within the broader innovation framework has been steadily increasing, reflecting its essential role in the sustainable development of future cities (Vasconcellos Oliveira, 2021). An increasing amount of research underscores that the ideas, methodologies, processes, and resources supporting social innovation are particularly effective for advancing the achievement of the Sustainable Development Goals (SDGs) (Dionisio, 2023a). As a result, the aims and methods of urban sustainability and social innovation are more interconnected (Dionisio, 2023). Such transformations may be initiated either through top-down institutional strategies or bottom-up grassroots initiatives, evolving dynamically in response to contextual demands and subsequently becoming integrated into citizens' daily activities and working environments. Empirical research on the determinants of smart city development identifies public-private partnerships (PPPs) as one of the five critical enablers that enhance urban smartness (Myeong, 2018). Importantly, this perspective redefines citizens as not merely participants of policy outcomes but also as co-creators and active contributors within both policymaking and governance processes. In alignment with this view, Kassim (2022) asserts that the essential requirements for achieving sustainable development are inherently contained within the framework of social innovation.

Furthermore, social innovation refers to the integration of market-oriented practices within the operations of governmental and nonprofit entities (Krasnopolskaya & Minnigaleeva, 2017). Central to this process is the active participation and collaboration of diverse stakeholders (Duan, 2019). Although AI may not serve as a comprehensive solution for issues in government–stakeholder relations, it represents a powerful instrument for enhancing the efficiency and responsiveness of municipal governments in policy formulation and decision-making, particularly when combined with socially innovative strategies. An expanding range of research has highlighted the significance of AI in fostering social innovation (Dargham & Hachimi, 2021), and has examined the relationship between social innovation and smart decision-making (Gibson & Roelvink, 2012). Building upon existing literature, the present study posits that several direct relationships depend on context-specific factors. Accordingly, the following hypotheses were developed based on previous empirical and theoretical insights.

$H_{2:}$ Employing big data from AI has a positive impact on social innovation in future cities.

$H_{3:}$ Social innovation has a positive influence on smart decision-making processes within future cities.

$H_{4:}$ Using big data from AI has a positive influence on smart decision-making in future cities mediated by social innovation.Internal Threats within the IoT

The IoT has experienced rapid evolution, marked by substantial advancements in communication and software technologies (Kumar, 2019), substantially altering daily lives and initiating an age of interconnected smart systems. Although remarkable milestones have been achieved across various fields, the IoT revolution remains an ongoing process (Abed & Anupam, 2023). Recent research has examined critical challenges to its advancement, including the impact of persistent cyberattacks on public trust, the diversity of communication protocols supporting IoT infrastructures, and the growing integration of AI (de Azambuja, 2023). The inherent vulnerabilities within these systems expose them to exploitation by hackers, potentially resulting in the hijacking or manipulation of IoT networks (Sadhu, 2022). As Hassan and Awad (2018) observed, users who perceive heightened risks associated with internal IoT threats often tend to maintain reliance on familiar digital services, even when faced with complex issues and limited perceived benefits. Building on this perspective, it is reasonable to assume that internal IoT vulnerabilities may weaken the synergistic interaction between AI and social innovation, thereby constraining the technology's broader societal potential. Thus, the following hypotheses were developed:

$H_{5:}$ The relationship between AI and social innovation is influenced by moderation via internal threats to the IoT. As the level of these threats increases, the positive relationship between AI and social innovation becomes weakened (less noticeable).

Moreover, the fundamental principles of the IoTs encompass universal accessibility—ensuring connectivity for all individuals, through any means, and at any time—representing what Langley (2021) describes as the essence of global connectivity. However, such widespread accessibility inherently amplifies the potential security vulnerabilities within IoT systems (Almuraqab & Jasimuddin, 2017). Empirical evidence from numerous studies demonstrates that security and privacy concerns are likely to exert the greatest influence on the acceptance and sustainability of IoT applications in the future development of smart cities (Williams, 2022). These vulnerabilities within IoT operations may influence or constrain decision-making processes in urban governance. Accordingly, this study posits that the internal vulnerabilities or latent risks within IoT infrastructures may compromise the efficacy of AI-driven decision-making in future

$H_{6:}$ Internal threats to the IoT moderate the positive impact between AI and smart decision-making; the positive relationship is weakened when they are high (more prevalent).

MATERIALS AND METHODES

The main objective of this study was to develop a comprehensive analytical framework that clarifies the connection between AI and smart decision-making, incorporating social innovation as a mediating variable and internal IoT threats as a moderating element. Gender, age, and educational attainment were included as control variables to account for potential demographic influences. The research further sought to examine community perceptions of AI's influence on decision-making processes. To ensure the robustness of construct reliability and validity, the selection of participants was closely aligned with the overall research design. Accordingly, a purposive sampling strategy—classified as a non-probability sampling technique—was employed to select respondents with relevant knowledge and experience pertinent to the study's aims.

Research Sample and Data Collection

The participants in the study were located in Shenzhen, China, and aged between 20 and 65 years. Table 1 summarizes the demographic characteristics of the respondents. All online questionnaires were administered and collected anonymously to ensure confidentiality. Out of 402 distributed questionnaires, 351 were considered valid, yielding a response rate of 87.31%. The survey employed a five-point Likert scale, where 1 denoted "strongly disagree" and 5 denoted "strongly agree." Respondents were asked to evaluate all constructs included in the study and to rate their views on the role of AI in future smart cities, the significance of social innovation, and potential internal threats posed by the IoTs to public services and smart decision-making processes.

Table 1. Demographic Characteristics of Respondent Sample.

No.	Characteristics	Category	N (=351)	Percentage (%)
1	Gender	Male	198	56
		Female	153	44
2	Age	20-35	121	34
		36-50	154	44
		51-65	76	22
3	Education	High school	43	12
		Vocational degree	91	26
		Bachelor's degree	126	36
		Master's degree and above	91	26

Measurement

In this study, AI was assessed using four items adapted from Müller and Bostrom (2016), which capture participants' perceptions of AI's trustworthiness and its broader social implications. Social innovation was measured through four items drawn from Hoelscher (2015), designed to evaluate users' perceptions of smart service delivery within the context of smart cities. The construct of internal threats to the IoT was operationalized using measurement items developed by Abomhara (2015), focusing on perceived security and privacy concerns. Finally, smart decision-making was measured with four items adapted from Klug and Kmoch (2015), addressing the application of emerging technologies in decision-making processes. The detailed measurement items for all constructs are presented in Appendix A.

Data Analysis

Both SPSS and AMOS were employed to analyse the empirical data in this study. The use of multiple regression analysis in SPSS has increasingly been recognised as an advanced and adaptable alternative for traditional statistical techniques, owing to its enhanced analytical capabilities. Recent developments have expanded its functionality to incorporate confirmatory analysis, non-linear effects, as well as mediating and moderating interactions (Rosopa & Stone-Romero, 2008). Meanwhile, AMOS was used specifically to perform confirmatory factor analysis (CFA), enabling the estimation and validation of the measurement model for all latent constructs included in this research.

Figure 1 depicts the proposed study model, which initially demonstrates a direct relationship between AI and smart decision-making. However, the introduction of social innovation into the model altered the direct linear correlation into a mediated relationship. This analytical shift aligns with the theoretical constructs of moderated mediation and mediated moderation as delineated by Muller, Judd, and Yzerbyt (2005). In their formulation, M_0 represents the moderator variable(s), Me denotes the mediator variable(s), and εi indicates the measurement error term in each regression equation, as articulated in the analytical framework presented by Muller, Judd, and Yzerbyt (2005):

$$Y=\beta_{40}+\beta_{41}\chi+\beta_{42}M_0+\beta_{43}\chi M_0+\varepsilon_4 \quad (1)$$

The above formula elucidates the moderating of the correlation between the IV (X) and the DV (Y), which is frequently referred to as the overall treatment effect (path γ).

$$Me=\beta_{50}+\beta_{51}\chi+\beta_{52}M_0+\beta_{53}\chi M_0+\varepsilon_5 \quad (2)$$

The formula denotes the moderation of the correlation between the IV and the mediator, specifically referred to as the path α.

$$Y=\beta_{60}+\beta_{61}\chi+\beta_{62}M_0+\beta_{63}\chi M_0+\beta_{64}Me+\beta_{65}MeM_0+\varepsilon_6 \quad (3)$$

The formula illustrates the moderating of the correlation between the IV and DV (path A), as well as the correlation between the mediator and the DV (path β).

RESULTS AND DISCUSSION

Common Method Variance: Harman Single Factor

Previous research indicates that employing a singular data source—such as a common respondent, evaluator, or reviewer—for both independent and dependent variables may result in self-report bias (MacKenzie &

Podsakoff, 2012). In other words, respondents' subjective tendencies, whether positive or negative toward the research topic, can systematically influence their responses, thereby inflating or deflating observed associations. Therefore, evaluating for common method variance (CMV) is essential to determine the degree to which such biases may affect the validity of the results.

The current study examined CMV using Harman's single-factor test (Harman, 1976). This method entails conducting an exploratory factor analysis (EFA) by loading all measurement items into a single unrotated factor (Podsakoff, 2003). The emergence of a singular latent factor that explains over 50% of the total variation signifies considerable common method bias.

Using the principal component extraction method, the analysis constrained the solution to a single factor. The results revealed that the first factor accounted for 39.4% of the total variance, falling short of the 50% threshold. This indicates that common method bias is not a substantial issue in this study.

Model for Measuring

Data distribution testing: Skewness and Kurtosis

Measures of skewness and kurtosis were employed to assess whether the observed indicators met the assumption of normality (Kline, 2011). These statistical measures help determine the extent to which a distribution deviates from an ideal normal curve, thereby facilitating additional descriptive analysis. According to Kline (2011), skewness values within the range of −3 to +3 and kurtosis values between −10 and +10 are generally considered acceptable for a normal distribution. As shown in Table 2, the skewness values (ranging from 0.106 to 1.326) and kurtosis values (ranging from 0.849 to 1.574) both fall within these acceptable thresholds, indicating that the data distribution can be regarded as approximately normal.

Table 2. Assessments of Reliability and Validity.

Variables	Items	Convergent Validity		Internal Consistency Reliability		Normal distribution	
		Factor loading (λ) ≥0.70	Average Variance Extracted (AVE>0.50)	Cronbach's Alpha (α)	Composite Reliability (CR>0.70)	Skewness	Kurtosis
AI	AI1	0.978	0.776	0.961	0.924	-0.587	-1.574
	AI2	0.965				-0.734	-1.301
	AI3	0.867				-0.812	-1.029
	AI4	0.886				-0.413	-0.995
Social innovation	SI1	0.858	0.634	0.912	0.864	0.432	1.108
	SI2	0.813				0.857	1.275
	SI3	0.832				0.898	0.849
	SI4	0.912				0.902	0.917
Internal IoT threats	IOT1	0.731	0.678	0.879	0.857	-1.326	1.213
	IOT2	0.822				-1.198	-0.934
	IOT3	0.924				-0.980	-0.916
Smart decision-making	SDM1	0.778	0.690	0.854	0.823	0.265	-0.955
	SDM2	0.832				0.293	-1.264
	SDM3	0.900				-0.106	-1.342
	SDM4	0.811				0.312	-1.483

Reliability and Validity of Measuring Variables

To further assess the reliability and validity of the measurement model, all item factor loadings surpassed the recommended threshold of 0.70, indicating strong item–construct correlations. Convergent validity was evaluated using the Average Variance Extracted (AVE), with a minimum acceptable threshold of 0.50 (Cheung, 2023). Composite Reliability (CR) was also calculated for each construct, where values above 0.70 denote acceptable internal consistency (Cheung, 2023). As shown in Table 2, the factor loadings varied from 0.731 to 0.978, the AVE values spanned from 0.634 to 0.776, and the CR values ranged from 0.823 to 0.924. The results collectively affirm that the assessment items demonstrated great reliability and convergent validity, indicating a high level of consistency and robustness in the operationalization of the study's constructs.

Descriptive Statistics, Pearson Correlation Coefficient, and Discriminant Validity

The Fornell–Larcker criterion is the most widely acknowledged method for assessing discriminant validity within measurement models. According to this criterion, the square root of a construct's Average Variance Extracted (AVE) must exceed its correlations with any other construct. This criterion ensures that each construct in the model is empirically distinct from others, hence validating the sufficiency of discriminant validity (Henseler, 2015). As presented in Table 3, the AVE values for all constructs surpass the Pearson correlation coefficients, suggesting adequate discriminant validity across the measurement model. Furthermore, the variance inflation factor (VIF) values obtained in this study were all below the standard threshold of 10, signifying that multicollinearity is not an issue within the dataset.

Table 3. Descriptive Statistics, Correlation, and Discriminant Validity

Variables	Mean (M)	Standard Deviation (SD)	AI	SI	IOT	SDM	GEN	AGE	EDU
AI	3.810	1.154	0.765						
SI	3.845	0.967	0.682**	0.804					
IOT	2.993	1.402	0.610**	0.577**	0.732				
SDM	3.342	1.453	0.741**	0.609**	0.711**	0.897			
GEN	1.123	0.849	0.397**	0.214**	0.312**	0.512**	1		
AGE	1.596	0.759	0.098	0.445**	0.241**	-0.098	0.454**	1	
EDU	2.657	0.897	0.076	0.098	0.276**	0.142**	0.421**	0.067	1

Note: The diagonal elements, which are highlighted in bold, represent the square roots of the AVE values. The correlations between the variables are presented below the diagonal. The statistical significance levels used in this study are denoted as *p < 0.05 and **p < 0.01 (two-tailed).

Table 3 presents the descriptive statistics, data reliability, and correlations among the variables. The mean value for AI is 3.810 and the SD is 1.154, indicating the respondents concurred with the use of AI in future cities for decision-making. In terms of social innovation, the mean is 3.845 and the SD is 0.967, indicating that the majority of respondents believed in social innovation for decision-making utilising AI-generated big data. Regarding smart decision-making, the mean is 3.334 and the SD is 1.453, meaning that respondents strongly concurred with the idea of smart decision-making in smart cities via SI and AI. With a correlation of (r = 0.741 **; p < 0.01), it could be discovered that AI and smart decision-making are positively correlated.

Hypotheses Testing

Testing for Direct Effects and Mediation Model

The study employed Hayes' PROCESS 4 macro-model to assess H1, H2, H3, and H4 hypotheses. The results from H1 (β =0.401, p= 0.000, 95% CI excludes zero, 0.286 to 0.387) provide evidence in support of a correlation between AI and SDM. Specifically, the results demonstrate that the utilisation of big data sets derived from AI has a statistically significant and positive impact on SDM. As predicted in hypothesis 2, the relationship between AI and social innovation was validated (β =0.825, p= 0.000, 95% CI =0.352, 0.162). The results revealed that AI has a significant positive effect on social innovation. Moreover, there was a significant positive relationship between social innovation and smart decision-making (β =0.454, p= 0.000, 95% CI =0.311, 0.067). The bootstrap methodology is commonly used in mediation analysis because of its great attributes and robustness (Beasley, 2014). The employment of 5,000 bootstrap resamples resulted in the mediation analysis producing the most robust outcome. All three hypotheses (H1, H2, and H3) turned out to be supported. To employ a form of resampling technique on the data that is currently available to derive outcomes and gain a thorough understanding of the underlying population was the primary focus of bootstrapping (Saravanan, 2020). An indirect positive connection between AI and smart decision-making has been identified through social innovation (β =0.278, 95% CI =0.201, 0.112), this proved that H4 was valid.

Table 4. Evaluating Both the Direct and Mediation Effects among Variables

Model		*β*	SE	*t*	*P*	LLCI	ULCI	R^2
95% CI (Bootstrap)								
1	Mediator variable							
	AI	0.825	0.032	8.965	0.000	0.352	0.162	0.401

2	Dependent variable: SDM							
	AI	0.401	0.098	7.921	0.000	0.286	0.387	0.623
	SI	0.454	0.101	7.243	0.000	0.311	0.067	
Results obtained through the execution of bootstrapping methods reveal the indirect effect of AI on SDM mediated via SI		0.278	0.055			0.201	0.112	

- Model of Moderation Testing (The Internal Threats to the IoT)

Via the moderating effect of the internal threats of the IoT, both the correlation between AI and SI (H5) along with the correlation between AI and SDM (H6) were examined using the PROCESS macro (model 8), with gender, age, and level of education serving as confounded variables. The outcomes are displayed in Table 5.

Table 5. The Evaluation of the Moderation Model

Model			***β***	**SE**	***t***	***P***	**LLCI**	**ULCI**	**R^2**
Bootstrap 95% CI									
1	mediator variable								
	AI		-0.643	-0.067	-11.356	0.000	-0.746	-0.512	0.448
	Internal threats of IOT		-0.138	-0.096	4.327	0.001	-0.092	-0.030	
	AI, Internal threats of IOT (interaction)		-0.101	0.031	-5.633	0.000	-0.312	-0.077	
	Control variable	GEN	-0.431	0.067	-6.889	0.000	-0.649	-0.528	
		AGE	0.215	0.048	10.976	0.000	0.309	0.331	
		EDU	0.311	0.073	4.223	0.001	0.114	0.301	
The conditional direct effect of AI on SI									
Internal threats of IOT (-1SD)			0.674	0.056	10.911	0.561	-0.310	0.309	
Internal threats of IOT (+1SD)			-0.590	-0.035	-15.908	0.000	-0.081	-0.201	
2	Dependent variable: SDM								
	AI		0.291	0.034	5.103	0.001	0.318	0.441	0.296
	SI		0.121	0.051	4.998	0.000	0.301	0.379	
	Internal threats of IOT		-0.512	-0.078	-9.768	0.001	-0.675	-0.406	
	AI, Internal threats of IOT (interaction)		0.097	0.097	3.711	0.001	0.170	0.204	
	Control variable	GEN	-0.539	0.133	-4.902	0.000	-0.707	-0.324	
		AGE	-0.193	0.043	-4.191	0.000	-0.260	-0.089	
		EDU	0.503	0.065	7.768	0.000	0.489	0.790	
The conditional direct effect of AI on SDM									
Internal threats of IOT (-1SD)			0.231	0.061	3.981	0.001	0.342	0.453	
Internal threats of IOT (+1SD)			0.049	0.059	2.101	0.001	0.192	0.301	
Bootstrapped indirect effects result (via SI)									
Index of moderated mediation			-0.021	-0.003			-0.009	-0.028	
The conditional indirect effect of AI on SDM (via SI)									
Internal threats of IOT (-1SD)			0.308	0.031			0.192	0.085	
Internal threats of IOT (+1SD)			0.291	0.049			0.097	0.095	

The analysis revealed a significant relationship between the use of AI integrated with big data and the presence of internal IoT threats, which continued to significantly affect SI even after controlling for demographic characteristics (β =−0.101, p≤ 0.000). This finding supports H5, which asserts that internal IoT threats mitigate the positive relationships inside the model. Subsequent analysis of the conditional direct effects of AI on technological integration indicated that the negative correlation rises under conditions of higher internal IoT threats (β =−0.590, p≤ 0.000), whereas the correlation is not statistically significant (β =−0.674, p≥ 0.05) when internal threats are low. These results provide additional empirical support for H5. Moreover, the study identified a significant interaction effect between AI and internal IoT threats on SDM ($\beta = -0.097$, $p \leq 0.001$). The conditional direct effect analysis reinforces H6, demonstrating that the positive relationship between AI and SDM is stronger under low internal IoT threat settings ($\beta = 0.291$, $p < 0.001$) , although significantly diminished when internal risks are heightened ($\beta = 0.049$, $p \leq 0.001$).

CONCLUSION

Despite the widespread deployment of AI in contemporary urban contexts, a deeper analytical approach is crucial to enhance municipal governance and support better public decision-making. This study enriches the discourse on the developing intersection of AI and SDM in future smart city research by analyzing these complex relationships across many economic and governance circumstances. The study seeks to produce specific and theoretically important insights by integrating interaction variables. Specifically, this work addresses a key research gap by investigating the mediating role of SI in the relationship between AI and SDM, while also introducing the moderating influence of internal IoT threats. Through this dual focus, the research highlights both the mediating significance of SI and the potential vulnerabilities influencing AI-driven governance. Empirical analysis revealed that SI serves as a critical mediator between AI and SDM. Initially, the direct relationship between AI and SDM was examined, followed by an assessment of SI as a mediating construct linking the independent (AI) and dependent (SDM) variables. The findings indicate a substantial direct correlation between AI and SDM, alongside a complete mediating effect of SI, highlighting its pivotal role in enhancing the efficacy of AI-driven decision-making in smart city administration.

Furthermore, the rapid expansion of the IoT has been followed by an increase in internal security concerns, warranting their consideration as moderating variables in our study. Many of these threats arise from vulnerabilities at the device level, often exploited through cybercrime or the incorrect use of system resources. In line with the current findings, it is essential that IoT infrastructures be developed to provide both usability and strong security management. Building user confidence is crucial for the effective implementation of AI-driven systems, enabling individuals to benefit from smart decision-making while alleviating privacy and security concerns. Accordingly, future urban leaders must proactively tackle these challenges by strengthening policy frameworks and ensuring the seamless implementation of cybersecurity measures. This requires substantial efforts to mitigate IoT vulnerabilities through effectively integrated institutional protocols and methods (Mikalef, 2021). As AI technologies advance—propelled by extensive data analytics, intricate algorithms, and improved processing power—they are becoming more integrated into daily life and significantly impacting SDM. The findings of this study contribute significantly to both the theoretical and practical understanding of AI-enabled decision-making processes. These findings are essential for informed policymaking and for promoting the adoption and long-term sustainability of smart public services.

REFERENCES

Abed, A. K., & Anupam, A. (2023). Review of security issues in Internet of Things and artificial intelligence-driven solutions. *SECURITY AND PRIVACY*, *6*(3), e285. https://doi.org/10.1002/spy2.285

Abomhara, M., Department of Information and Communication Technology, University of Agder, Norway, Kien, G. M., & Department of Information and Communication Technology, University of Agder, Norway. (2015). Cyber Security and the Internet of Things: Vulnerabilities, Threats, Intruders and Attacks. *Journal of Cyber Security and Mobility*, *4*(1), 65–88. https://doi.org/10.13052/jcsm2245-1439.414

Ahad, M. A., Paiva, S., Tripathi, G., & Feroz, N. (2020). Enabling technologies and sustainable smart cities. *Sustainable Cities and Society*, *61*, 102301. https://doi.org/10.1016/j.scs.2020.102301

Allahar, H. (2020). What are the Challenges of Building a Smart City? *Technology Innovation Management Review*, *10*(9), 38–48. https://doi.org/10.22215/timreview/1388

Allam, Z., & Dhunny, Z. A. (2019). On big data, artificial intelligence and smart cities. *Cities*, *89*, 80–91. https://doi.org/10.1016/j.cities.2019.01.032

Almuraqab, N., & Jasimuddin, S. (2017). Factors that Influence End-Users' Adoption of Smart Government Services in the UAE: A Conceptual Framework. *Electronic Journal of Information Systems Evaluation*, *20*, 11–23.

Alvarez, R. (2017). The Relevance of Informational Infrastructures in Future Cities. *Field Actions Science Reports. The Journal of Field Actions*, *Special Issue 17*, Article Special Issue 17.

Ardill, N., & Lemes de Oliveira, F. (2018). Social innovation in urban spaces. *International Journal of Urban Sustainable Development*, *10*(3), 207–221. https://doi.org/10.1080/19463138.2018.1526177

Arruda, D., & H. Madhavji, N. (2017). The Role of Big Data Analytics in Corporate Decision-making: *Proceedings of the 6th International Conference on Data Science, Technology and Applications*, 28–37. https://doi.org/10.5220/0006402300280037

Beasley, T. M. (2014). Tests of Mediation: Paradoxical Decline in Statistical Power as a Function of Mediator Collinearity. *Journal of experimental education*, *82*(3), 283–306. https://doi.org/10.1080/00220973.2013.813360

Berntzen, L., Johannessen, M., & El-Gazzar, R. (2018). *Smart Cities, Big Data and Smart Decision-making Understanding 《Big Data》 in Smart City Applications*.

Bokhari, S. A. A., & Myeong, S. (2022). Use of Artificial Intelligence in Smart Cities for Smart Decision-Making: A Social Innovation Perspective. *Sustainability*, *14*(2), Article 2. https://doi.org/10.3390/su14020620

Castro-Arce, K., & Vanclay, F. (2019). Transformative social innovation for sustainable rural development: An analytical framework to assist community-based initiatives. *Journal of Rural Studies*, *74*. https://doi.org/10.1016/j.jrurstud.2019.11.010

Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2023). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management*. https://doi.org/10.1007/s10490-023-09871-y

Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. *International Journal of Information Management*, *60*, 102383. https://doi.org/10.1016/j.ijinfomgt.2021.102383

Dargham, M., & Hachimi, H. (2021). Artificial Intelligence & the emergence of social innovation Case of the Group 《Crédit Agricole》 in Morocco. *2021 7th International Conference on Optimization and Applications (ICOA)*, 1–5. https://doi.org/10.1109/ICOA51614.2021.9442663

Dash, B., & Sharma, P. (2022). Role of Artificial Intelligence in Smart Cities for Information Gathering and Dissemination—A Review. *Academic Journal of Research and Scientific Publishing*, *4*, 58–75. https://doi.org/10.52132/Ajrsp.e.2022.39.4

de Azambuja, A. J. G., Plesker, C., Schützer, K., Anderl, R., Schleich, B., & Almeida, V. R. (2023). Artificial Intelligence-Based Cyber Security in the Context of Industry 4.0—A Survey. *Electronics*, *12*(8), Article 8. https://doi.org/10.3390/electronics12081920

de Jong, M. D. T., Neulen, S., & Jansma, S. R. (2019). Citizens' intentions to participate in governmental co-creation initiatives: Comparing three co-creation configurations. *Government Information Quarterly*, *36*(3), 490–500. https://doi.org/10.1016/j.giq.2019.04.003

Deakin, M., & Al Waer, H. (2011). From intelligent to smart cities. *Intelligent Buildings International*, *3*(3), 140–152. https://doi.org/10.1080/17508975.2011.586671

Diakaki, C., Grigoroudis, E., Kabelis, N., Kolokotsa, D., Kalaitzakis, K., & Stavrakakis, G. (2010). A multi-objective decision model for the improvement of energy efficiency in buildings. *Energy*, *35*(12), 5483–5496. https://doi.org/10.1016/j.energy.2010.05.012

Dionisio, M., de Souza Junior, S. J., Paula, F., & Pellanda, P. C. (2023a). The role of digital social innovations to address SDGs: A systematic review. *Environment, Development and Sustainability*. https://doi.org/10.1007/s10668-023-03038-x

Dionisio, M., de Souza Junior, S. J., Paula, F., & Pellanda, P. C. (2023b). The role of digital social innovations to address SDGs: A systematic review. *Environment, Development and Sustainability*, 1–26. https://doi.org/10.1007/s10668-023-03038-x

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. *International Journal of Information Management*, *48*, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Gibson, K., & Roelvink, G. (2012). Social innovation for community economies. *Social Innovation and Territorial Development*, 25–38.

Harman, H. H. (1976). *Modern Factor Analysis*. University of Chicago Press.

Hassan, A. M., & Awad, A. I. (2018). Urban Transition in the Era of the Internet of Things: Social Implications and Privacy Challenges. *IEEE Access*, *6*, 36428–36440. https://doi.org/10.1109/ACCESS.2018.2838339

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hoelscher, M., Mildenberger, G., Bund, E., & Gerhard, U. (2015). A Methodological Framework for Measuring Social Innovation. *Historical Social Research / Historische Sozialforschung*, *40*, 48–78. https://doi.org/10.12759/hsr.40.2015.3.48-78

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, *61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

Jensen, J. (2016). A Review of Public–Private Partnership Activities in Health System Strengthening. *The Role of Public-Private Partnerships in Health Systems Strengthening: Workshop Summary*. National Academies Press (US). https://www.ncbi.nlm.nih.gov/books/NBK373286/

Kassim, E. S., Zamzuri, N. H., Jalil, S. A., Mohamed Salleh, S., Mohamad, A., & Abdul Rahim, R. (2022). A Social Innovation Model for Sustainable Development: A Case Study of a Malaysian Entrepreneur Cooperative (KOKULAC). *Administrative Sciences*, *12*(3), Article 3. https://doi.org/10.3390/admsci12030103

Kim, H. M., Sabri, S., & Kent, A. (2021). Smart cities as a platform for technological and social innovation in productivity, sustainability, and livability: A conceptual framework. *Smart Cities for Technological and Social Innovation*, 9–28. https://doi.org/10.1016/B978-0-12-818886-6.00002-2

Kline, R. B. (2011). *Principles and practice of structural equation modeling, 3rd ed* (xvi, 427). Guilford Press.

Klug, H., & Kmoch, A. (2015). Operationalizing environmental indicators for real time multi-purpose decision making and action support. *Ecological Modelling*, *295*, 66–74. https://doi.org/10.1016/j.ecolmodel.2014.04.009

Krasnopolskaya, I., & Minnigaleeva, G. (2017). Social Innovation. A. Farazmand, *Global Encyclopedia of Public Administration, Public Policy, and Governance* (1–6). Springer International Publishing. https://doi.org/10.1007/978-3-319-31816-5_3012-1

Kumar, S., Tiwari, P., & Zymbler, M. (2019). Internet of Things is a revolutionary approach for future technology enhancement: A review. *Journal of Big Data*, *6*(1), 111. https://doi.org/10.1186/s40537-019-0268-2

Langley, D. J., van Doorn, J., Ng, I. C. L., Stieglitz, S., Lazovik, A., & Boonstra, A. (2021). The Internet of Everything: Smart things and their impact on business models. *Journal of Business Research*, *122*, 853–863. https://doi.org/10.1016/j.jbusres.2019.12.035

Li, C., Chen, Y., & Shang, Y. (2022). A review of industrial big data for decision making in intelligent manufacturing. *Engineering Science and Technology, an International Journal*, *29*, 101021. https://doi.org/10.1016/j.jestch.2021.06.001

Lien, C.-H., & Cao, Y. (2014). Examining WeChat users' motivations, trust, attitudes, and positive word-of-mouth: Evidence from China. *Computers in Human Behavior*, *41*, 104–111. https://doi.org/10.1016/j.chb.2014.08.013

Lopes, N. V. (2017). Smart governance: A key factor for smart cities implementation. *2017 IEEE International Conference on Smart Grid and Smart Cities (ICSGSC)*, 277–282. https://doi.org/10.1109/ICSGSC.2017.8038591

Lytras, M. D., Visvizi, A., Chopdar, P. K., Sarirete, A., & Alhalabi, W. (2021). Information Management in Smart Cities: Turning end users' views into multi-item scale development, validation, and policy-making recommendations. *International Journal of Information Management*, *56*, 102146. https://doi.org/10.1016/j.ijinfomgt.2020.102146

Ma, Y., Ping, K., Wu, C., Chen, L., Shi, H., & Chong, D. (2019). Artificial Intelligence powered Internet of Things and smart public service. *Library Hi Tech*, *38*(1), 165–179. https://doi.org/10.1108/LHT-12-2017-0274

MacKenzie, S. B., & Podsakoff, P. M. (2012). Common Method Bias in Marketing: Causes, Mechanisms, and Procedural Remedies. *Journal of Retailing*, *88*(4), 542–555. https://doi.org/10.1016/j.jretai.2012.08.001

MacKinnon, D., Krull, J., & Lockwood, C. (2001). MacKinnon DP, Krull JL, Lockwood CM. Equivalence of the mediation, confounding and suppression effect. *Prevention science : the official journal of the Society for Prevention Research*, *1*, 173–181. https://doi.org/10.1023/A:1026595011371

MacKinnon, D. P., Krull, J. L., & Lockwood, C. M. (2000). Equivalence of the Mediation, Confounding and Suppression Effect. *Prevention science : the official journal of the Society for Prevention Research*, *1*(4), 173.

Mikalef, P., Fjørtoft, S. O., & Torvatn, H. Y. (2019). Artificial Intelligence in the Public Sector: A Study of Challenges and Opportunities for Norwegian Municipalities. I. O. Pappas, P. Mikalef, Y. K. Dwivedi, L. Jaccheri, J. Krogstie, & M. Mäntymäki, *Digital Transformation for a Sustainable Society in the 21st Century* (267–277). Springer International Publishing. https://doi.org/10.1007/978-3-030-29374-1_22

Mikalef, P., Lemmer, K., Schäfer, C., Ylinen, M., Fjørtoft, S., Torvatn, H., Gupta, M., & Niehaves, B. (2021). Enabling AI capabilities in government agencies: A study of determinants for European municipalities. *Government Information Quarterly*, *39*, 101596. https://doi.org/10.1016/j.giq.2021.101596

Millard, J., & Fucci, V. (2023). The role of social innovation in tackling global poverty and vulnerability. *Frontiers in Sociology*, *8*, 966918. https://doi.org/10.3389/fsoc.2023.966918

Mora, L., Deakin, M., Aina, Y., & Appio, F. (2020). *Smart City Development: ICT Innovation for Urban Sustainability* (1–17). https://doi.org/10.1007/978-3-319-71061-7_27-1

Muller, D., Judd, C. M., & Yzerbyt, V. Y. (2005). When moderation is mediated and mediation is moderated. *Journal of Personality and Social Psychology*, *89*(6), 852–863. https://doi.org/10.1037/0022-3514.89.6.852

Müller, V. C., & Bostrom, N. (2016). Future Progress in Artificial Intelligence: A Survey of Expert Opinion. V. C. Müller, *Fundamental Issues of Artificial Intelligence* (555–572). Springer International Publishing. https://doi.org/10.1007/978-3-319-26485-1_33

Myeong, S., Jung, Y., & Lee, E. (2018). A Study on Determinant Factors in Smart City Development: An Analytic Hierarchy Process Analysis. *Sustainability*, *10*(8), Article 8. https://doi.org/10.3390/su10082606

Nastjuk, I., Trang, S., & Papageorgiou, E. I. (2022). Smart cities and smart governance models for future cities. *Electronic Markets*, *32*(4), 1917–1924. https://doi.org/10.1007/s12525-022-00609-0

Peng, Z.-R., Kaifa, L., Liu, Y., & Zhai, W. (2023). The Pathway of Urban Planning AI: From Planning Support to Plan-Making. *Journal of Planning Education and Research*. https://doi.org/10.1177/0739456X231180568

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *The Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Rahmani, A. M., Azhir, E., Ali, S., Mohammadi, M., Ahmed, O. H., Yassin Ghafour, M., Hasan Ahmed, S., & Hosseinzadeh, M. (2021). Artificial intelligence approaches and mechanisms for big data analytics: A systematic study. *PeerJ Computer Science*, *7*, e488. https://doi.org/10.7717/peerj-cs.488

Raisch, S., & Krakowski, S. (2020). Artificial Intelligence and Management: The Automation-Augmentation Paradox. *Academy of Management Review*. https://doi.org/10.5465/2018.0072

Rosopa, P. J., & Stone-Romero, E. F. (2008). Problems with detecting assumed mediation using the hierarchical multiple regression strategy. *Human Resource Management Review*, *18*(4), 294–310. https://doi.org/10.1016/j.hrmr.2008.07.009

Sadhu, P. K., Yanambaka, V. P., & Abdelgawad, A. (2022). Internet of Things: Security and Solutions Survey. *Sensors (Basel, Switzerland)*, *22*(19), 7433. https://doi.org/10.3390/s22197433

Salari, O. (2022). *THE ROLE OF BIG DATA IN BUSINESS AND DECISION MAKING*. 84–100. https://doi.org/10.5281/zenodo.6613311

Saravanan, V., Berman, G. J., & Sober, S. J. (2020). Application of the hierarchical bootstrap to multi-level data in neuroscience. *Neurons, behavior, data analysis and theory*, *3*(5), https://nbdt.scholasticahq.com/article/13927-application-of-the-hierarchical-bootstrap-to-multi-level-data-in-neuroscience.

Satalkina, L., & Steiner, G. (2022). Social Innovation: A Retrospective Perspective. *Minerva*, *60*(4), 567–591. https://doi.org/10.1007/s11024-022-09471-y

Scholl, H., & Alawadhi, S. (2016). Creating Smart Governance: The key to radical ICT overhaul at the City of Munich. *Information Polity*, *21*, 21–42. https://doi.org/10.3233/IP-150369

Shahid, K., Hassan, M., Husnain, A., Mukhtar, S., Shahid, K., Hassan, M., Husnain, A., & Mukhtar, S. (2022). Information and Communication Technologies for New Generation of Sustainable Smart Cities. *Sustainable Smart Cities—A Vision for Tomorrow*. IntechOpen. https://doi.org/10.5772/intechopen.107251

Sharif, R. A., & Pokharel, S. (2022). Smart City Dimensions and Associated Risks: Review of literature. *Sustainable Cities and Society*, *77*, 103542. https://doi.org/10.1016/j.scs.2021.103542

Thakker, D., Mishra, B. K., Abdullatif, A., Mazumdar, S., & Simpson, S. (2020). Explainable Artificial Intelligence for Developing Smart Cities Solutions. *Smart Cities*, *3*(4), Article 4. https://doi.org/10.3390/smartcities3040065

van Noordt, C., & Misuraca, G. (2020). *Evaluating the impact of artificial intelligence technologies in public services: Towards an assessment framework*. https://doi.org/10.1145/3428502.3428504

Vasconcellos Oliveira, R. (2021). Social Innovation for a Just Sustainable Development: Integrating the Wellbeing of Future People. *Sustainability*, *13*(16), Article 16. https://doi.org/10.3390/su13169013

Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S. D., Tegmark, M., & Fuso Nerini, F. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. *Nature Communications*, *11*(1), Article 1. https://doi.org/10.1038/s41467-019-14108-y

Vrabie, C. I., & Tirziu, A.-M. (2016). E-participation – a Key Factor in Developing Smart Cities. *MPRA Paper*, Article 77707. https://ideas.repec.org//p/pra/mprapa/77707.html

Williams, P., Dutta, I. K., Daoud, H., & Bayoumi, M. (2022). A survey on security in internet of things with a focus on the impact of emerging technologies. *Internet of Things*, *19*, 100564. https://doi.org/10.1016/j.iot.2022.100564

Appendix A

No.	Constructs	Measurement items	
1	Artificial Intelligence	AI1	From my perspective, AI exerts a significant impact on society.
		AI2	Regarding public services, I believe the government ought to implement AI.

		AI3	I have great confidence in the accuracy of the information that AI provides.
		AI4	In my view, AI exacerbates the problem of unemployment in certain areas.
2	Social Innovation	SI1	From my perspective, social entrepreneurship is dedicated to improving the community rather than pursuing financial gain.
		SI2	The living standards of people in urban areas are, in my opinion, raised by local and regional development.
		SI3	I believe that design thinking enables policymakers and decision-makers to make better city planning decisions.
		SI4	I believe that in social economies, people and social goals take precedence over capital.
3	Internal threats to the IoT	IoT1	In my opinion, the majority of IoT devices function unattended by humans and operate autonomously, making them vulnerable to physical attacks from potential attackers.
		IoT2	I think that most IoT components primarily utilise wireless networks for communication, which can be vulnerable to eavesdropping by attackers seeking to access confidential information.
		IoT3	In my view, most IoT components lack the ability to handle complex security schemes due to their limited power and computing capabilities.
4	Smart Decision-making	SDM1	From my perspective, local government employs contemporary technologies instead of traditional approaches for decision-making.
		SDM2	I believe the local government collects a substantial amount of data on the potential opportunity to make more informed decisions for the public.
		SDM3	In my perspective, when local governments encounter a challenging circumstance, they maintain a positive outlook on discovering a favorable resolution for the public and carefully evaluate all the feasible options for decision-making.
		SDM4	In my view, when it comes to making decisions that affect the public, the local government doesn't wait until it's too late.