IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 23 September 2023, accepted 21 October 2023, date of publication 23 October 2023, date of current version 2 November 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3327174

RESEARCH ARTICLE

The Impact of AI Applications on Smart Decision-Making in Smart Cities as Mediated by the Internet of Things and Smart Governance

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This work was supported in part by the Ministry of Education, Republic of Korea; and in part by the National Research Foundation of Korea under Grant NRF-2022S1A5C2A03093690.

ABSTRACT Plenteous research has been undertaken on the direct effects of artificial intelligence (AI) on smart decision-making. However, little attention has been paid to contextual factors such as the Internet of Things (IoT) and smart governance that mediate the relationship between AI and smart decision-making. This research investigates direct, mediating, and parallel-sequential multiple mediating interactions between AI, the IoT, smart governance, and smart decision-making. We used a self-structured survey to collect cross-sectional data from citizens in the Republic of Korea, and 516 responses were examined using SmartPLS structural equation modeling (PLS-SEM). A parallel-sequential multiple mediator framework is assessed using the Hayes Process Model with bootstrapping. Our results reveal a substantial and favorable multi-mediating effect from the IoT and smart governance on the relationship between AI applications and smart decision-making, as predicted. Previous scholars have investigated a few factors that influence decision-making, but our research contributes to the literature of applied and social sciences, including traditional decision theory, by examining the impact of multi-mediating factors on smart decision-making. This study presents both theoretical and practical implications for scholars and policymakers engaged in the development of smart cities. Additionally, this study provides recommendations for future research.

INDEX TERMS Artificial intelligence, Internet of Things, big data, smart governance, smart decision-making, parallel-sequential multi-mediating effect.

I. INTRODUCTION

Artificial intelligence (AI), its novel discipline, the potential for transformation, and its effects on smart governance in cities and on decision-making have been a subject of discussion both in practice and debate for the last couple of decades [1], [2], [3], [4], [5], [6]. AI is gaining influence and becoming a necessity for daily life and organizational operations as technology takes significant leaps in empowering AI development [7].

AI, defined as deep convergence of cognitive technologies that contain machine learning, computer vision, natural language processing, and robotics, recently got a boost as measured by the intensity of investment, the number of academic publications covering it, and regulatory interest in it. The hurdle to overcome in comprehending new socio-economic conditions developed by the extensive adoption of AI is indicated by its widespread consequences, bridging almost every domain from healthcare [8], [9], labor markets [10], [11], education [12], and the Internet of Thing (IoT) [13], to smart governance [3], [14], social innovation [15], human rights protection [16], [17], and decision-making [18], [19]. Nevertheless, the difficulty for government is a potentially disastrous double-blind trial: its responsibility is to shield its inhabitants from possible algorithmic problems while enticing them with enhanced self-competence,

The associate editor coordinating the review of this manuscript and approving it for publication was Bo Pu.

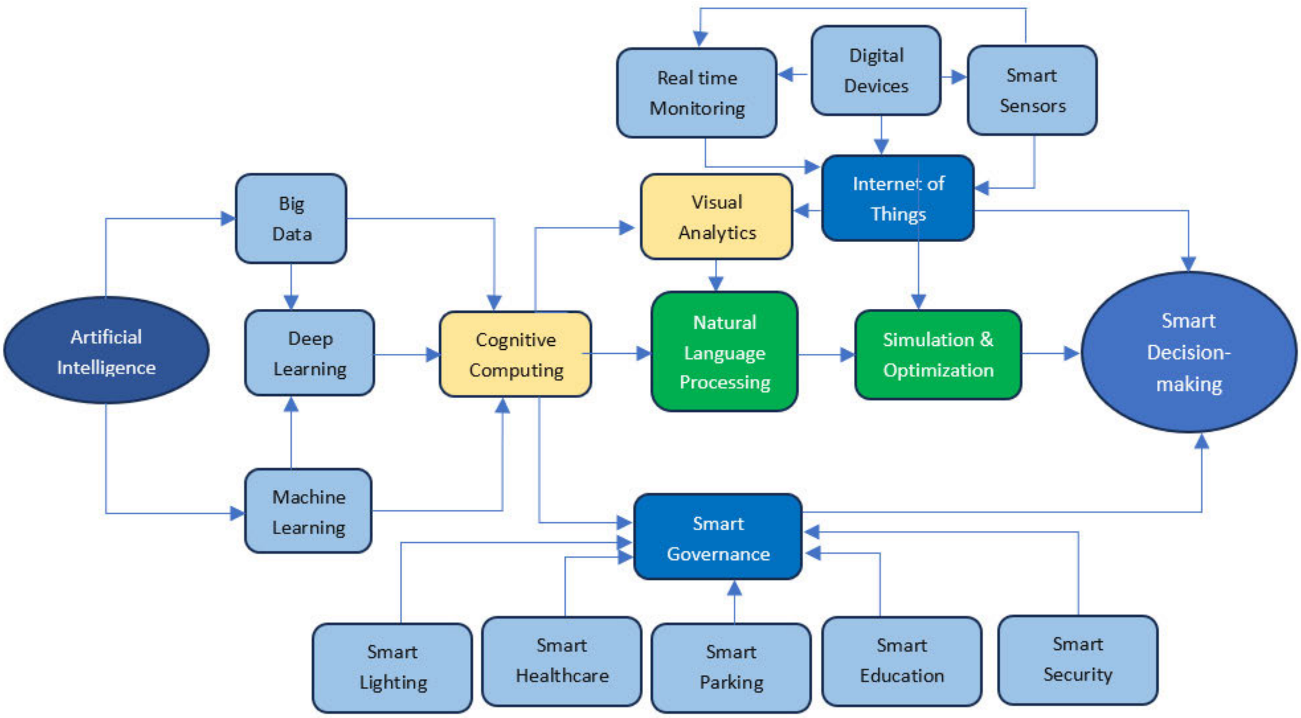

FIGURE 1. **Conceptual framework of impacts by AI applications, the IoT, and smart governance on smart decision-making.**

or more specifically, to administer algorithms while governed by those same algorithms.

AI applications in smart cities for policy and decision-making have become a crucial topic in smart governance and urban governance [2], [20], [21]. Similarly, another stream of researchers is explaining the use of AI to promote governance through the Internet of Things [13]. The IoT consists of thousands of devices connected via an internet-based standard system that works in the cloud and allows people to access and create data from anywhere; many of these approaches are used in governance [22]. Furthermore, IoT systems comprise communication channels that are easily approachable amongst a broad spectrum of gadgets, such as surveillance cameras, vehicles, sensors, actuators, and home appliances. The AI-assisted, IoT-empowered smart city has caught the attention of numerous intellectuals, industry professionals, and public officials because it may force government agencies to capitalize on information and on communication technology to administer public matters efficiently and transparently and for better decision-making about secure environments [23], [24].

The Internet of Things and smart governance are important factors influencing the correlation between AI and smart decision-making. Traditional decision theory describes how to determine the most rational and prudent substitute for a specific incident that will address the intended implication. Decision-makers evaluate different possibilities and identify their strong and weak points. Applying traditional decision theory, the objective of this study is to investigate how AI, with the assistance of the IoT and smart governance, impacts smart decision-making. Prior research focused mostly on the direct impact of AI applications on decision-making, but very little attention has been paid to situational or contextual factors that may affect this relationship. For instance, Bokhari and Myeong [19] investigated the mediating role of social innovation between the linking of AI application and smart decision-making. Alloulbi and Alzubi [25] examined a moderated mediated model of internal threats from the IoT and technology anxiety on the relationship between artificial intelligence applications for smart decision-making in smart cities.

The data sample for this study was collected using a survey conducted in the Republic of Korea. Using SmartPLS version 4, we employed structural equation modeling (SEM) to empirically investigate several hypotheses. The findings demonstrated a positive impact from AI applications on smart decision-making, as well as the role of IoT systems and smart governance in mediating the relationship between AI applications and smart decision-making. This study contributes to the decision theory literature by investigating the multiple mediating effects of AI, the IoT, and smart governance. This study will help scholars and public managers in local government understand the need for artificial intelligence in governance systems, and how it can be utilized efficiently and effectively for decision-making, service delivery, and information gathering in a smart government. Figure 1 demonstrates a conceptual framework for the impacts from AI applications, the IoT, and smart governance on smart decision-making.

The rest of the study is organized as follows. A literature review with hypothesis development is presented in Section II. Our research methodology, including data collection and data analysis, is described in Section III. Section IV presents analysis results along with tables. Discussions of the study's implications and limitations plus directions for future research are in Section V. Finally, concluding remarks are in Section VI.

II. LITERATURE REVIEW AND THE HYPOTHESES

A. AI APPLICATIONS IN DECISION-MAKING

Artificial intelligence does not have a universally accepted definition. It is commonly considered a machine's capacity to acquire knowledge from experience, adapt to different input factors, and accomplish human-like activities. The concepts of artificial intelligence and artificial intelligence systems were first applied in the 1950s, with subsequent upward and downward trends (so-called *AI springs* and *AI winters*). AI was revitalized by the accessibility and strength of big data, due to its simultaneous development with improved computing storage capacities and mega-fast data processing devices [4]. Thus, AI is growing rapidly within big organizations after decades of expectations and pledges [26]. The adoption of AI-enabled solutions in organizations is growing exponentially [27], and AI is consolidating organizations [28]. The modern generation of AI techniques has advanced an organization's capacity to utilize data to make decisions while significantly reducing the cost of making those decisions [29].

Smart cities emerged as a logical consequence of (and are transformed by) the decisions they incorporate [30], [31], and thus, are signified by their strategic plans [32]. Cities function in a dynamic environment, and although decisions impact stakeholders directly or indirectly [33], [34], [35], smart decision-making is a challenging and dynamic process [36], [37], [38], [39]. Numerous public and private organizations globally create open data sources readily accessible over the internet that can be employed for data analytics and decision-making. The true advantage of big data is not in the enormous amount of information, but in the development of advanced AI technologies, including machine learning, that can evaluate sophisticated and immense datasets far beyond what humans have done previously. This type of progress also provides valuable information for decision-making [40].

A smart city is a dynamic, structured, and highly sophisticated interconnected endeavor that consists of embedded sensors, data gathering, and infrastructure surveillance to optimize decision-making [3], [41], [42]. Literature has shown that computation and interpreting big data by utilizing AI is a significant approach to improving decision-making in smart cities [43], [44]. Because the thrust for the latest phenomenon of *smart* is made highly conceivable through the acquisition of genuine datasets and analysis of these data to derive an understanding of how cities reshape, adapt, and respond to dynamic environments [2], [40], technological concepts related to AI systems have been empowering cities to become smart. Hence, we hypothesize the following.

Hypothesis 1. AI applying big data implemented by the city government improves smart decision-making.

B. AI APPLICATIONS ON THE INTERNET OF THINGS

The Internet of Things is a vague concept that includes operators, process automation, computing capabilities, and a substantial number of devices that are connected over the internet. Consequently, each digital platform can identify configurations, interact with other platforms, document and analyze data, and respond accordingly. The final stretch of adequate behavior is entirely reliant on the current processing phase. The extent of computations or interventions that an IoT platform can perform determines its actual smartness. A non-intelligent IoT gateway can have significant limitations and is unlikely to transform in parallel through the data. A stronger IoT platform, in contrast, would include artificial intelligence and may support the intended goal of automation and adaptation. Voice assistants (Alexa, Siri, Google Assistant), robotics (Sophia, robotic kitchens), smart devices (ovens, skybell, lights, automobiles), and the industrial IoT (primer, Plutoshift) are just a few illustrations of modern IoT solutions using artificial intelligence [45].

According to Roman et al., concerns about security and privacy would be important predictors of IoT adoption in the evolution of a smart city [46]. Their study also concluded that when the issues are much more sophisticated and the potential advantages unsatisfactory, people will continue with the conventional services they are familiar with. Moreover, because the core concept behind the IoT is multinational integration (access to anyone) and convenience (access them in any way, anytime), the challenges that might influence IoT solutions are tremendous [47], [48]. However, Kumar et al. proposed a framework to address potential security threats to IoT systems [49]. Likewise, a framework called AITalk was proposed, which enables a programmer to efficiently affix the AI system to existing IoT applications through a graphical user interface, thereby providing a user-friendly platform for conveniently incorporating AI into IoT systems without needing any scripting endeavors [50]. Finally, previous studies in the literature concluded that IoT applications function efficiently with the assistance of AI applications [13], [45], [51], [52]. Thus, we developed the following hypothesis.

Hypothesis 2. AI application contributes positively to IoT systems.

C. THE MEDIATING ROLE OF THE IoT

Several academics previously discovered that tangible AI devices such as sensors could improve the intelligence and smartness of smart cities, particularly when connected to certain other tangible gadgets such as the IoT [45]. Even more evident is that decision-making is core to the IoT [52], [53]; it is about decision information processing using sensor technology such as big data, real-time analytics in data processing, and further reactions contributing to real-time decision-making [54]. Certainly, decision-making in smart cities through the IoT has become an integral aspect of artificial intelligence [55], [56] through its enhanced capabilities in speech synthesis, video, and voice identification, as well as social media and language comprehension.

Devices are deployed in the IoT to sense physical phenomena like weather, temperature, and emotional processes. Depending on the information, user behavior and beliefs might even be identified adequately, which is critical in city government decision-making [57]. Currently, innovative sensor solutions that have evolved and developed recently, such as video surveillance, radar systems, and GPS-enabled information connectors, allow us to gain insights into the behavioral characteristics of city inhabitants during their everyday routines [58]. Furthermore, information collected by sensors may be transmitted to the cloud, where it would be compiled by big data platforms and utilized to make smart decisions about services, mobility, security, the environment, and quality of life in the city [59], [60]. Consequently, we formulate the following hypotheses based on previous studies in the literature that found AI applications influence IoT systems positively [13], [52], and that IoT systems assist policymakers in making smart decisions [55], [61].

Hypothesis 3. IoT applications affect smart decision-making positively.

Hypothesis 4. IoT systems mediate the relationship between AI applications and smart decision-making positively.

D. AI APPLICATIONS IN SMART GOVERNANCE

Although little attention has been paid to AI in the public sector until now, there is an upward trend as proven by the growth in studies of AI, smart government, and e-governance [62], [63], [64], [65], [66], [67]. The benefits of AI applications in the public sector across several government departments have been highlighted in these publications while admitting that the intensive potential of AI is hampered by technical, organizational, and policy complications [62]. Scholars have revealed the important role of AI in promoting smart governance, in making a city smart, and in supporting good quality of life in practice. Scholl and AlAwadhi emphasized how AI-enabled governance allows cities to collaborate to create smart services that no city can supply alone [67]. For example, a smart-home load-control system was proposed that encourages a demand response from observing the situation [68]. Similarly, AI applications in smart cities encourage data collection using sensors and other sources to enhance urban safety governance [69]. For instance, the government of South Korea employed AI to deal with the COVID-19 pandemic by encouraging proactive information exchange, helping citizens comprehend the issue, and implementing the safety protocols released [70].

Sensor and network technologies are critical in smart governance [65], [66]. Sensors entail little change in governance because they focus on using the evidence collected (the data) rather than on institutional reorganization. Many layers of data on human mobility and behavior, environmental performance, and the flow of infrastructure and services are continuously monitored. These data assist cities in becoming more inventive in their decision-making, and they allow governments to offer data for both public and private use. The smart city utilizes sensors and technology connected to the IoT to integrate all the data into a reliable surveillance system, helping city managers to govern smartly [71]. Based on previous studies in the literature between AI and governance [63], [64], [67], we developed the following hypothesis.

Hypothesis 5. AI application contributes positively to smart governance.

E. THE MEDIATING ROLE OF SMART GOVERNANCE

Although decision-making can be assisted through several ICT tools such as databases and dashboards, AI stands out because of three design characteristics: (1) it automates learning and decision-making processes through advanced mathematical representations of problems; (2) the more data it collects, the more it learns and adapts its behavior to the new information collected by updating its decision heuristics; and (3) it processes the input data using speeds and high dimensionality that greatly outstrip human cognition [72]. Artificial intelligence focuses on using sensor applications to collect, capture, and save real-time data, helping cities to better understand how to tackle real-life difficulties. It also allows the government to place a greater focus on sound decision-making and well-informed execution of those decisions [73], [74], [75].

AI provides a mechanism for improving government power structures by overcoming widespread deficiencies in administrative decision-making. These common deficiencies include inaccurate forecasting of important functions like granting small-business loans, discretionary favoritism like inconsistent police citation rates, and varying quality in decisions because of disparities in accuracy among executives or over time due to mental fatigue [4]. AI can assist in solving such challenges by being more consistent in terms of reducing discrepancies and partiality, by being more accurate and more cost-effective in terms of reducing labor costs related to repetitive jobs, and by being less susceptible to corruption in terms of establishing a greater connection between input data and decisions [72].

Cities like Bristol and Manchester in the United Kingdom are at the frontline of this data-driven city-development revolution. All sensor data are anonymized before being made

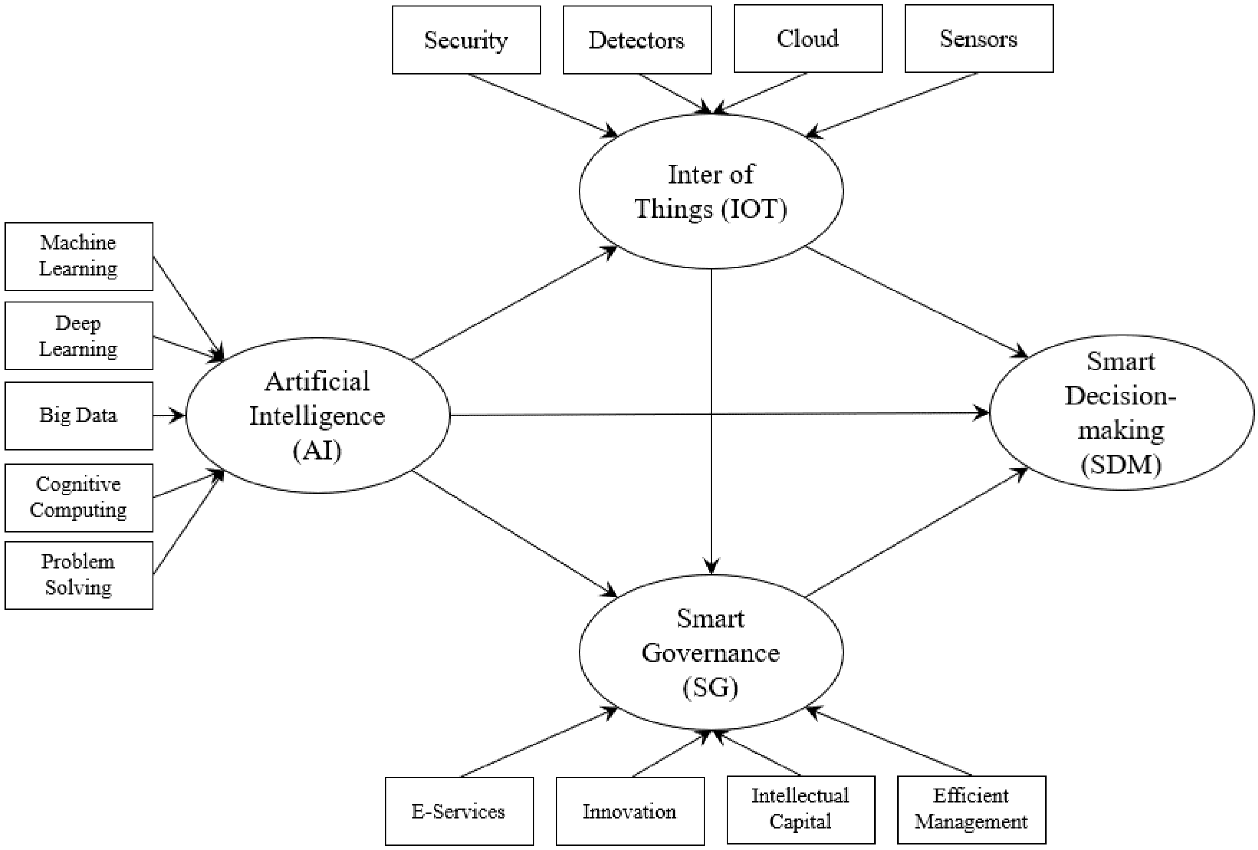

FIGURE 2. **Parallel-sequential multi-mediating conceptual framework for assessing AI influence on smart decision-making.**

public via an open data site for what is called the Bristol Open Programmable City. Using digital platforms to collect real-time data and stream it is becoming a prominent smart governance approach [76]. The presence of AI-embedded Internet of Things platforms, the cloud, data analytics, and universal connectivity has twisted the notion of smart governance into a reality, particularly providing medical services to deal with COVID-19 [77]. Although government leaders worldwide wish to make their cities smarter, the security and privacy of the data collected for AI and the IoT have become a challenge for smart cities. Such applications for better decision-making require protecting the collected data from disruption, modification, annihilation, inspection, and numerous other malicious activities, which is possible thanks to blockchain for security [60], [78]. Furthermore, a positive transformation was found in the perception of the impact of information technology on policy decision-making procedures through AI applications among government managers in smart cities [79]. Hence, we propose these hypotheses.

Hypothesis 6. Smart governance affects smart decision-making positively.

Hypothesis 7. Smart governance mediates the relationship between AI applications and smart decision-making positively.

F. MULTI-MEDIATING EFFECTS

According to the 1997 World Forum on Smart Cities, about 50,000 cities and towns worldwide were expected to launch smart projects within the subsequent 10 years [80]. Technology and human-driven approaches are the two major methods applied in the literature to aid discussions on smart cities. "Decision-making sits at the heart of the administration," according to Simon [81], a legendary figure in the domains of governance and AI. Moreover, AI applications through IoT systems in smart governance have become a key aspect of cities facing the enormous challenges of ensuring social inclusion, sustainability, public health, prosperity, and safety [82]. When cities face such challenges, they implement numerous concepts to transform into smart cities, but this process involves various AI strategies generally promoted by urban politicians who formulate the governing systems and by other professionals worldwide [82]. AI is helping to solve these challenges by providing systems that improve public health, safety, and government services [62].

Based on our literature review, this study identifies hypotheses regarding the impact of artificial intelligence, the IoT, and smart governance on smart decision-making. First, the application of sensors in smart governance leads to smart and informed decision-making [4]. Second, artificial intelligence used in smart administration and electronic governance

TABLE 1. Summary of research hypotheses.

Hypotheses	Description
Hypothesis 1	AI applying Big Data implemented by the city government improves smart decision-making
Hypothesis 2	AI application contributes positively to IoT systems
Hypothesis 3	IoT applications affect smart decision-making positively
Hypothesis 4	IoT systems mediate the relationship between AI applications and smart decision-making positively
Hypothesis 5	AI application contributes positively to smart governance
Hypothesis 6	Smart governance affects smart decision-making positively
Hypothesis 7	Smart governance mediates the relationship between AI applications and smart decision-making positively
Hypothesis 8	IoT applications affect smart governance positively
Hypothesis 9	IoT systems mediate the relationship between AI applications and smart governance positively
Hypothesis 10	IoT systems and smart governance have a multi-mediating effect on the relationship between AI applications and smart decision-making.

leads to higher usage of IoT devices for better service delivery [13], [45]. Third, using the Internet of Things (IoT) helps city managers to govern smartly to provide efficient services in their cities [71]. Lastly, smart governance in urban areas using AI and IoT gadgets will impact city governors positively so they can make decisions smartly [69].

Based on previous studies in the literature, we developed the following hypotheses about the multiple mediating roles for the IoT and smart governance between AI and smart decision-making.

Hypothesis 8. IoT applications affect smart governance positively.

Hypothesis 9. IoT systems mediate the relationship between AI applications and smart governance positively.

Hypothesis 10. IoT systems and smart governance have a multi-mediating effect on the relationship between AI applications and smart decision-making.

A summary of all proposed hypotheses developed for this study is in Table 1. Figure 2 shows our research framework, where artificial intelligence is the independent variable, smart decision-making is the dependent variable, and IoT and smart governance are measured as mediating variables. Our research framework indicates a significant direct effect from artificial intelligence on decision-making, but when the IoT and smart governance were included in the model, the positive linear relationship became a significant mediating impact.

III. RESEARCH METHODOLOGY

The predominant objective of this research is to develop and examine a model for a deep understanding of the relationship between AI application and smart decision-making with mediating roles from IoT systems and smart governance in smart cities. Cross-sectional research was conducted to investigate the research hypotheses developed in this study. It comprised studies of the perceptions in communities about the role of AI in smart decision-making. Primary data for this study were collected from the general public in the Republic of Korea, and 535 individuals in total responded to emailed, posted, and online questionnaires that assisted us to increase our construct reliability and validity [83].

TABLE 2. Demographics of participants.

Attribute	Distribution	Frequency	%
Gender	Male	326	63.18
	Female	190	36.82
Age	18 to 30 years	219	42.44
	31 to 45 years	254	49.22
	46 to 60 years	27	5.23
	More than 60 years	16	3.11
Education	High School	68	13.18
	College	164	31.78
	University	210	40.70
	Postgraduate	74	14.34
Profession	Public Servant	72	13.95
	Employee	224	43.41
	Student	106	20.54
	Unemployed	93	18.02
	Retired	21	4.08

A. DATA SCREENING AND PRE-ANALYSIS

Sample data for this study were collected in accordance with its main purpose. The data sampling fieldwork was conducted between September and October 2022. Out of the 535 completed surveys, 19 were excluded due to incomplete information. Consequently, the final sample consisted of 516 responses from people with different demographic characteristics. Table 2 shows the majority of the participants (63.18%) were male and 36.82% were female. Similarly, 42.44% were 18 to 30 years old, 49.22% were between 31 and 45 years old, 5.23% were between 46 and 60, with only 3.11% older than 60. Furthermore, the survey showed that 13.18% of the respondents had only completed their high school education, 31.78% had obtained a college certificate, 40.70% had a university degree, and 14.34% had completed graduate studies. Among the 516 participants, 13.95% were engaged in public service, 43.41% were employed in the private sector, 20.54% were enrolled as students, 18.02% were either unemployed or working part-time, and 4.08% were retired. This study included specific demographic characteristics as control variables to determine whether these factors generated a direct influence on the decision-making process. On average, Cronbach's alpha was 0.70, indicating that the inter-rater reliability among various respondents was acceptable. Given that the single responses were drawn from a random sample of all participants, it is impossible that they would significantly compromise the study's validity. No missing values were detected in responses provided by any of the participants.

TABLE 3. Measurement model results - construct reliability, validity, and multicollinearity estimation.

Variable	Item	S.F.L	VIF	Skewness	Kurtosis	α	CR	AVE	rho_A
Artificial Intelligence	AI1	0.944	3.259	-0.007	-0.803	0.898	0.927	0.718	0.909
	AI2	0.695	1.642	-0.611	0.582				
	AI3	0.806	3.304	0.165	-1.074				
	AI4	0.896	2.552	-1.482	-0.188				
	AI5	0.875	2.301	-0.440	-0.570				
Internet of Things	IoT1	0.814	2.418	1.921	-1.548	0.877	0.916	0.732	0.905
	IoT2	0.895	2.961	0.635	-1.049				
	IoT3	0.789	2.027	-0.501	0.236				
	IoT4	0.916	3.073	-0.007	-0.803				
Smart Governance	SG1	0.843	2.097	-1.503	-0.095	0.839	0.903	0.757	0.878
	SG2	0.941	3.021	-1.170	-0.040				
	SG3	0.821	1.899	-0.614	-0.250				
Smart Decision-making	SDM5	0.735	1.985	-1.690	-0.111	0.929	0.948	0.786	0.938
	SDM1	0.952	2.181	-0.440	-0.570				
	SDM2	0.844	2.625	-1.576	0.015				
	SDM3	0.936	1.957	-1.482	-0.188				
	SDM4	0.946	1.677	-0.611	0.582				

Note: S.F.L = Standardized Factor Loadings; VIF = Variance Inflation Factor; α = Cronbach's alpha; CR = Composite Reliability; AVE = Average Variance Extracted.

We applied a subsequent statistical estimation structure to examine the mediating effect of the Internet of Things and smart governance on the relationship between AI applications and smart decision-making while accounting for potential confounding factors that may affect the adoption of AI for smart decision-making.

$$\text{SDM} = \beta_0 + \beta_1 AI + \beta_2 IoT + \beta_3 CONTROLS + \varepsilon_1$$
$$\text{SDM} = \beta_{10} + \beta_{11} AI + \beta_{12} SG + \beta_{13} CONTROLS + \varepsilon 2$$
$$\text{SDM} = \beta_{20} + \beta_{21} AI + \beta_{22} IoT + \beta_{23} SG + \beta_{24} CONTROLS + \varepsilon 3$$

In these statistical equations SDM stands for smart decision-making and AI refers to the mean score of artificial intelligence applications. Similarly, IoT represents an average score from adopting the Internet of Things; SG is the average score for smart governance; and the term CONTROLS encompasses the demographic characteristics of the user, including gender, age, and education.

B. COMMON METHOD BIAS EVALUATION

The probability of common method bias was evaluated using multiple methods. Initially, Harman's single-factor test was conducted for all factors [84]. The findings indicate that no individual factor was responsible for more than 50% of the variability, indicating no strong evidence of common method variance. Likewise, there was no indication of common method bias because no bivariate relationships between factors were considered highly significant ($r > 0.90$) [85]. Lastly, variance inflation factor (VIF) indices were assessed to conduct an in-depth examination for collinearity. A framework may be considered devoid of common method bias when all VIF indices are below or equal to 3.3 [86]. Table 3 shows VIF values below 3.3 demonstrating an absence of common method bias in the data.

C. NON-RESPONSE BIAS EVALUATION

This study employed a cross-sectional self-administered questionnaire as the primary instrument for data collection, which resulted in 516 usable responses. Consequently, it is essential to determine whether there is a possibility of non-response bias in the data, so we applied the extrapolation method to examine possible non-response bias. Armstrong and Overton stated that the extrapolation method is a highly recommended technique for evaluating non-response bias in cross-sectional research [87]. The method used for this study included performing a comparative analysis between early and late respondents to evaluate possible variations in mean values for each factor [87]. A t-test was conducted using IBM SPSS 24.0 to examine the mean values of the initial 100 respondents and the last 100 respondents. The outcomes showed no statistically significant variation ($p < 0.05$) in mean scores between the two segments. The outcomes indicated that non-response bias was not a concern for this study.

D. MEASUREMENT AND SCALES

The measurement items used for this study originated from previously validated studies. A five-point Likert scale ranging from 1 (strong disagreement) to 3 (neutral) to 5 (strong agreement) was used as the assessment method. The questionnaire was circulated in South Korea. Consequently, the scale items initially generated in English had to be translated into Korean.

The validity of scale items was maintained through a meticulous procedure to ensure the relevance and clarity of the questions. A group of six people (one professor, two doctoral candidates with significant research experience, and three experts) conducted a pretest to verify the validity and relevance of the items in the Korean context. The instrument was subjected to review by a panel of five specialists to discover possible shortcomings with the questionnaire structure. The

TABLE 4. Partial least square structural equation modeling results (direct effects).

	Original sample (O)	Sample mean	Std. Dev. (STDEV)	t-statistics (|O/STDEV|)	p-values	Supported or Not
Hypothesized Results						
Direct Effects						
Artificial Intelligence -> Smart Decision-making	1.185	1.185	0.028	42.275	0.000	Supported
Artificial Intelligence -> IoT	0.867	0.867	0.008	102.409	0.000	Supported
Internet of Things -> Smart Decision-making	-0.584	-0.584	0.036	16.125	0.000	Supported
Artificial Intelligence -> Smart Governance	0.320	0.323	0.052	6.206	0.000	Supported
Internet of Things -> Smart Governance	0.557	0.555	0.046	12.056	0.000	Supported
SG -> Smart Decision-making	0.276	0.276	0.04	6.958	0.000	Supported
Indirect Effects						
Artificial Intelligence -> Internet of Things -> Smart Governance	0.506	0.506	0.033	15.433	0.000	Supported
Artificial Intelligence -> Smart Governance -> Smart Decision-making	0.088	0.089	0.019	4.538	0.000	Supported
Artificial Intelligence -> Internet of Things -> Smart Governance	0.483	0.481	0.038	12.809	0.000	Supported
Internet of Things -> Smart Governance -> Smart Decision-making	0.153	0.153	0.025	6.123	0.000	Supported
Artificial Intelligence -> Internet of Things -> Smart Governance -> Smart Decision-making	0.133	0.132	0.021	6.222	0.000	Supported
Non-hypothesized Results						
Gen -> Artificial Intelligence	-1.064	-1.067	0.096	11.097	0.000	Supported
Gen -> Internet of Things	-0.563	-0.562	0.047	12.015	0.000	Supported
Gen -> Smart Governance	-0.622	-0.623	0.055	11.266	0.000	Supported
Gen -> Smart Decision-making	-0.181	-0.179	0.034	5.265	0.000	Supported
Age -> Artificial Intelligence	0.243	0.243	0.045	5.391	0.000	Supported
Age -> Internet of Things	0.238	0.237	0.017	14.382	0.000	Supported
Age -> Smart Governance	-0.168	-0.168	0.021	7.864	0.000	Supported
Age -> Smart Decision-making	0.057	0.056	0.016	3.652	0.000	Supported
Edu -> Artificial Intelligence	-0.201	-0.200	0.031	6.534	0.000	Supported
Edu -> Internet of Things	-0.011	-0.010	0.022	0.498	0.619	Not
Edu -> Smart Governance	0.049	0.049	0.021	2.321	0.020	Supported
Edu -> Smart Decision-making	0.027	0.028	0.015	1.798	0.072	Not

SRMR = 0.062; NFI = 0.85
$R^2_{\text{(Smart Governance)}} = 0.721$; $Q^2 = 0.314$
$R^2_{\text{(Internet of Things)}} = 0.751$
$R^2_{\text{(Smart Decision-making)}} = 0.946$

scale items were altered slightly after receiving comments from the specialists to address semantic factors that can result from linguistic differences and to enhance the overall comprehension of the scale items.

Based on previous research into AI applications that were used to facilitate human decision-making [88], an AI applications scale was adopted from Bokhari and Myeong [19]. This scale was measured using five items: trustworthy information, influence on society, confidence in AI, contribution to unemployment, and AI use for public services. Similarly, the IoT scale was adapted from research by Tien [55]. This scale was measured using three items: usefulness, legitimacy, and novelty/originality. The construct of smart governance was adapted from Pereira et al. [75] This scale was measured using four items: public service facilities, stakeholder involvement in policy-making, excellence in departmental performance, and satisfaction in organizational structure for service provision. Finally, the smart decision-making scale was also adopted from research by Bokhari and Myeong [19]. This scale was measured using five items: use of cutting-edge technologies, big data collection, optimism of governors in difficult situations, use of all available alternatives, and timely decision-making without delay.

E. DATA ANALYSIS

SmartPLS was used to analyze the data sample for this research, and structural equation modeling was used to investigate our hypotheses. Research on social science in recent years has revealed a great reliance on SEM as one of the finest conventional methods to investigate topics in the social sciences [89]. Furthermore, PLS-SEM is considered one of the finest novel substitutes, compared to previous traditional analysis tools, because of numerous upgrades such as impact-performance matrix analysis, confirmatory analysis, non-linear impacts, and mediating and moderating impacts between independent and dependent variables [90].

IV. RESULTS

A. MEASUREMENT MODEL RESULTS

A preliminary exploratory factor analysis test was applied utilizing SmartPLS to check and exclude some indicators containing low outer loadings with their consistent construct. A total of 19 outer indicators were based on our research survey. We launched the software and adjusted it to a maximum of 300 iterations and seven stop criteria. Figure 3 presents the initial test results showing that none of the model indicators recorded a low factor loading on their relevant construct. Two indicators under smart governance had factor loadings less than the minimum threshold of 7.0 [90], so we excluded those indicators and continued with all the rest so the final procedure of the structural model would have better reliability and validity.

This study evaluated a suggested structural framework (specifically, a parallel-sequential multiple mediator model) by considering various measures, including overall explanatory power indicated by R^2 values, predictive relevance (Q^2 values), path coefficients (β values), bootstrapping procedure (t values), the parallel and sequential mediation approach [91], and a goodness of fit index. This study effectively extends prior research by Duan et al. [4] by verifying the suggested parallel-sequential multiple mediator framework. Figure 3 clearly summarizes the outcomes from the study's suggested structural model.

Next, we continued assessing reflective measurement models to test the reliability and validity of indicators. Factor loadings of indicators with a large value for communality (near 1) describe variables of better fit, and vice versa. A factor loading of more than 0.70 is satisfactory and a suitable fit [92]. Table 3 indicates the values for construct reliability and validity of each component. All values of average variance extracted (AVE), Cronbach's alpha (α), and composite reliability (CR) were greater than the threshold value of 7.0 [90]. We accepted the levels of convergent validity and internal-consistency reliability and concluded that these data are reliable to investigate the constructs as hypothesized and according to the commonality test. Hence, none of these items were found with a high load, especially on other constructs. The R^2 value of the respective endogenous construct describes an estimation of the analytical accuracy of the model and the variance explicated in each of the respective endogenous constructs in the model [89]. Normally, the R^2 value ranges from zero to one. The greater the R^2 value, the higher the predictive accuracy [90]. In Table 4, the endogenous latent variable (smart decision-making) has a coefficient of determination R^2 of 0.946, which means 94.5% of the total variance in smart decision-making can be explained by the IoT and smart governance exogenous variables. This variance approach has been used in numerous previous studies in the literature on social science [89], [90].

Finally, PLS-SEM does not have a universal goodness of fit index. The base point of model fit criteria values is not understood effectively. Therefore, blindfolding and bootstrapping statistical techniques are utilized to overcome such problems. Normally, the model fit index is not always evident in the results. However, some scholars recommended reporting SRMR and NFI as indicators for a model fit index because it compares predicted correlation and actual association based on real observations of the model. The SRMR value must not be higher than 0.08, and NFI must be between zero and one. The value of SRMR in our study was 0.062 (less than 0.08), and the NFI value was 0.85, which is close to 1, indicating a good model fit. The closer NFI is to 1, the better the fit.

B. STRUCTURAL EQUATION MODELING RESULTS

1) DIRECT EFFECTS

Figure 3 presents the results from structural equation modeling. The bootstrapping test method was used to investigate path coefficients by utilizing the partial least square approach for PLS-SEM relying on t-statistics applying t-test values. Since p-values of all path coefficients between predicted constructs (e.g., AI, the IoT, and smart governance) and the outcome construct (smart decision-making) were less than the α significance level of 0.05, and values of t-statistics were greater than 1.96 for all relations given in Table 4, we can say that SEM path coefficients are statistically significant. Detailed results of structural equation modeling can be detected.

Subsequently, we investigated the mediating impact of the IoT and smart governance between AI (the predictor construct) and smart decision-making (the outcome construct) using the bootstrapping technique and applying a 95% confidence level to 5000 subsamples to discover the SmartPLS-SEM mean and standard deviation [90]. Reviewing previous literature, there are three possibilities for the mediating impact of one construct on the association between predictor and outcome construct (no mediating impact, a partial mediating impact, and a full mediating impact) depending on t-statistics and p-values. Table 4 displays the direct effects and the indirect mediating and multi-mediating impacts of the constructs.

Results in Table 4 signify the direct and indirect significant relationships between all exogenous, endogenous, and mediating constructs in our research framework relying on t-statistics and p-values. This study's first hypothesis proposes a positive influence from AI application on smart decision-making. The results showed that AI has a direct impact on smart decision-making ($\beta = 1.185$; t-statistics $= 42.275$; $p < 0.01$) for H1. These results are consistent with the findings from previous research by Bokhari and Myeong [19]. Similarly, a positive effect on IoT systems from AI application is suggested with Hypothesis 2. The findings proved a direct effect from AI on the IoT with substantial values ($\beta = 0.867$; $t = 102.409$; $p < 0.01$) for H2 which are consistent with the findings from prior studies [13], [45]. Likewise, Hypothesis 3 suggests a positive impact from the IoT on smart decision-making, and the results in

TABLE 5. Hayes process model for parallel-sequential multiple mediating analysis.

Model	Std. (β)	Std. Dev.	t-values	p-values	LL 2.5% C.I.	UL 2.5% C.I.
Model 1: Mediating Role of IoT (AI → IoT → SDM)						
Artificial Intelligence → Internet of Things	0.6546	0.0375	17.4334	0.0000	0.5808	0.7284
Internet of Things → Smart Decision-making	0.5870	0.0282	20.7888	0.0000	0.6425	0.5315
Artificial Intelligence → Smart Decision-making (without a mediator)	1.3670	0.0303	45.1117	0.0000	1.3075	1.4266
Artificial Intelligence → Smart Decision-making (with a mediator)	0.3842	0.0418	BootLLCI 0.4711		BootULCI 0.3037	
Model 2: Mediating Role of SG (AI → SG → SDM)						
Artificial Intelligence → Smart Governance	0.4828	0.0667	7.2433	0.0000	0.3518	0.6137
Smart Governance → Smart Decision-making	0.3680	0.0191	19.2471	0.0000	0.3304	0.4056
Artificial Intelligence → Smart Decision-making (without a mediator)	1.3670	0.0303	45.1117	0.0000	1.3075	1.4266
Artificial Intelligence → Smart Decision-making (with a mediator)	0.1777	0.0305	BootLLCI 0.1208		BootULCI 0.2412	
Model 3: Mediating Role of IoT (AI → IoT → SG)						
Artificial Intelligence → Internet of Things	0.9574	0.0260	36.7826	0.0000	0.9063	1.0086
Internet of Things → Smart Governance	0.6158	0.0593	10.3916	0.0000	0.4994	0.7322
Artificial Intelligence → Smart Governance (without a mediator)	0.4828	0.0667	7.2433	0.0000	0.3518	0.6137
Artificial Intelligence → Smart Governance (with a mediator)	0.5896	0.0621	BootLLCI 0.4617		BootULCI 0.7100	
Model 4: Mediating Role of SG (AI → IoT → SG → SDM)						
Artificial Intelligence → Internet of Things	0.6546	0.0375	17.4334	0.0000	0.5808	0.7284
Internet of Things → Smart Governance	0.6158	0.0593	10.3916	0.0000	0.4994	0.7322
Smart Governance → Smart Decision-making	0.3680	0.0191	19.2471	0.0000	0.3304	0.4056
Internet of Things → Smart Decision-making (without a mediator)	0.5870	0.0282	20.7888	0.0000	0.6425	0.5315
Internet of Things → Smart Decision-making (with a mediator)	0.2266	0.0338	BootLLCI 0.1613		BootULCI 0.2945	
Bootstrapping Results for Specific Indirect Results (Preacher & Hayes)						
Artificial Intelligence -> Internet of Things -> Smart Governance	0.506	0.033	15.433	0.000		
Artificial Intelligence -> Smart Governance -> Smart Decision-making	0.088	0.019	4.538	0.000		
Artificial Intelligence -> Internet of Things -> Smart Governance	0.483	0.038	12.809	0.000		
Internet of Things -> Smart Governance -> Smart Decision-making	0.153	0.025	6.123	0.000		
Artificial Intelligence -> Internet of Things -> Smart Governance -> Smart Decision-making	0.133	0.021	6.222	0.000		
Final Results of Mediation Effects						**Final Results**
Artificial Intelligence -> Internet of Things -> Smart Governance						Partial Mediation
Artificial Intelligence -> Smart Governance -> Smart Decision-making						Partial Mediation
Artificial Intelligence -> Internet of Things -> Smart Governance						Partial Mediation
Internet of Things -> Smart Governance -> Smart Decision-making						Partial Mediation
Artificial Intelligence -> Internet of Things -> Smart Governance -> Smart Decision-making						Partial Mediation

Table 4 revealed a positive impact from the IoT on smart decision-making ($\beta = 0.584$; $t = 16.125$; $p < 0.01$) for H3, aligned with the finding from prior research [55], [61]. These findings explain the significant direct effects; hence, H1, H2, and H3 are supported substantially. Furthermore, confirming Hypothesis 5 (that AI applications have a positive impact on smart governance), the results validated a direct association between AI and smart governance ($\beta = 0.320$; $t = 6.206$; $p < 0.01$). Thus, H5 is supported significantly. Hypothesis 6 suggests a strong and significant positive impact from smart governance on smart decision-making. The results demonstrated a significant impact from smart governance on smart decision-making ($\beta = 0.276$; $t = 6.958$; $p < 0.01$) for H6. Likewise, a significant, positive, direct impact from the IoT on smart governance was found ($\beta = 0.557$; $t = 12.056$; $p < 0.01$) for H8, as predicted. Therefore, H6 and H8 are strongly and significantly supported. These finding are in accordance with the findings from previous research [63], [64], [67], [69], [79].

Nonetheless, it is critical to understand that simple indirect effects assessment does not adequately determine mediation in a multiple mediator framework [91]. Given the intricate and distinctive features of our developed theoretical framework (specifically, the parallel-sequential multiple mediator model), we implemented the methodology presented by Preacher and Hayes [91]. This method enables us to measure the degree to which our proposed mediators, such as the Internet of Things and smart governance, constitute full or partial mediators between AI applications and smart decision-making. The subsequent subsection provides a comprehensive illustration of our process for evaluating mediation. Additionally, to facilitate understanding for the readership, a brief overview of the hypothesis analysis is also presented.

The structural model in Figure 3 displays significant explanatory power, as evidenced by an R^2 value of 0.946. Hair et al. [92] argued that depending only on the R^2 value is inappropriate when measuring the parsimony of a structural

TABLE 6. Summary of research results.

Hypotheses	Essence	Results (Effects)	Factors of Influence	
			Positive Effect	Negative Effect
Hypothesis 1	Artificial Intelligence -> Smart Decision-making	Supported	Direct Impact	
Hypothesis 2	Artificial Intelligence -> IoT	Supported	Direct Impact	
Hypothesis 3	Internet of Things -> Smart Decision-making	Supported	Direct Impact	
Hypothesis 4	Artificial Intelligence -> Smart Governance	Supported	Direct Impact	
Hypothesis 5	Internet of Things -> Smart Governance	Supported	Direct Impact	
Hypothesis 6	SG -> Smart Decision-making	Supported	Direct Impact	
Hypothesis 7	Artificial Intelligence -> Internet of Things -> Smart Governance	Supported	Mediating Impact	
Hypothesis 8	Artificial Intelligence -> Smart Governance -> Smart Decision-making	Supported	Mediating Impact	
Hypothesis 9	Artificial Intelligence -> Internet of Things -> Smart Governance	Supported	Mediating Impact	
Hypothesis 10	Artificial Intelligence -> Internet of Things -> Smart Governance -> Smart Decision-making	Supported	Multi-mediating Impact	

model using the PLS-SEM framework. The suggested structural model was assessed for its predictive relevance using the Q^2 test [93]. The Q^2 value was estimated using a blindfolding method. Based on the findings of Hair et al. [92], a non-zero Q^2 value suggests that a particular structural model has substantial predictive relevance for its endogenous constructs. The results show that the structural model formulated in this study has a Q^2 value of 0.314, suggesting significant predictive relevance for smart decision-making.

2) INDIRECT EFFECTS

A key objective of this study is to evaluate the mediating impacts of IoT systems and smart governance on the connection between AI applications and smart decision-making. To examine the relationship between AI applications and smart decision-making, our suggested framework provides extensive parallel and sequential mediation. Previous scholars have developed a number of parallel, sequential, and parallel-sequential multiple mediating model techniques in this context [94]. Our suggested framework is a parallel-sequential multiple mediator framework that complies with the criteria established by Singh et al. [94]. Although the data in Table 4 have already proven the significance of the direct link, we hypothesize between AI applications and smart decision-making in H1, another independent analysis was conducted to evaluate the direct link between AI applications and smart decision-making without including mediators. Figure 4 presents the results of this evaluation. The result showed that AI applications have a very strong and considerable direct impact ($\beta = 0.953$; t = 373.203; $p < 0.01$) on smart decision-making.

Furthermore, Table 5 highlights the substantial parallel and sequential mediating effects of the Internet of Things and smart governance between the association of AI application and smart decision-making (H4, H7, H9, and H10). Nonetheless, the degree to which this represents full or partial mediation remains unresolved. To resolve this issue, we conducted more in-depth and elaborate mediation analyses. Baron and Kenny in [95] presented an imprecise approach for evaluating basic mediation models involving a single mediator [96]. However, several researchers such as Zhao et al. [97] criticized the mediation approach proposed by Baron and Kenny in [95], pointing out its limitations in explaining models with multiple mediators. Given the complexity and unique features of our suggested theoretical framework in Figure 1 (a parallel-sequential multiple mediating model [94] incorporating the Internet of Things and smart governance as mediators in the interaction between AI applications and smart decision-making), we decided to select and use the bootstrapping Hayes Process model advocated by Preacher and Hayes [91]. The assessment of multiple mediating models is viewed as a challenging task given the likelihood of collinearity issues highlighted in previous studies that are neglected among multiple mediators [91], [94], [97].

As portrayed in Model 1 of Table 5 (AI $\rightarrow$ IoT $\rightarrow$ SDM) AI application has a significant positive influence on smart decision-making ($\beta = 1.367$; t = 45.111; $p < 0.01$). In addition, the suggested mediator in this model (the Internet of Things) has a positive and substantial effect on smart decision-making ($\beta = 0.587$; t = 20.778; $p < 0.01$). The outcomes of bootstrapping confirmed that the confidence interval [0.471; 0.304] was not zero, and thereby, all of these findings are consistent with the conditions of a significant Internet of Things mediation effect between AI applications and smart decision-making [91]. These results strongly support H4. Likewise, Model 2 in Table 5 (AI $\rightarrow$ SG $\rightarrow$ SDM) illustrates a positive and substantial relationship between AI applications and smart decision-making ($\beta = 1.367$; t = 45.111; $p < 0.01$); smart governance (the suggested mediator in the model) also has a significant and positive relationship with smart decision-making ($\beta = 0.368$; t = 19.247; $p < 0.01$). Meanwhile, the findings from bootstrapping indicated that the confidence interval [0.121; 0.241] excluded zero, indicating that smart governance does, in fact, significantly mediate the relationship between AI applications and smart decision-making [91]. The findings in Model 2 support H7.

Model 3 in Table 5 (AI $\rightarrow$ IoT $\rightarrow$ SG) exemplifies a strong positive link between AI applications and smart governance

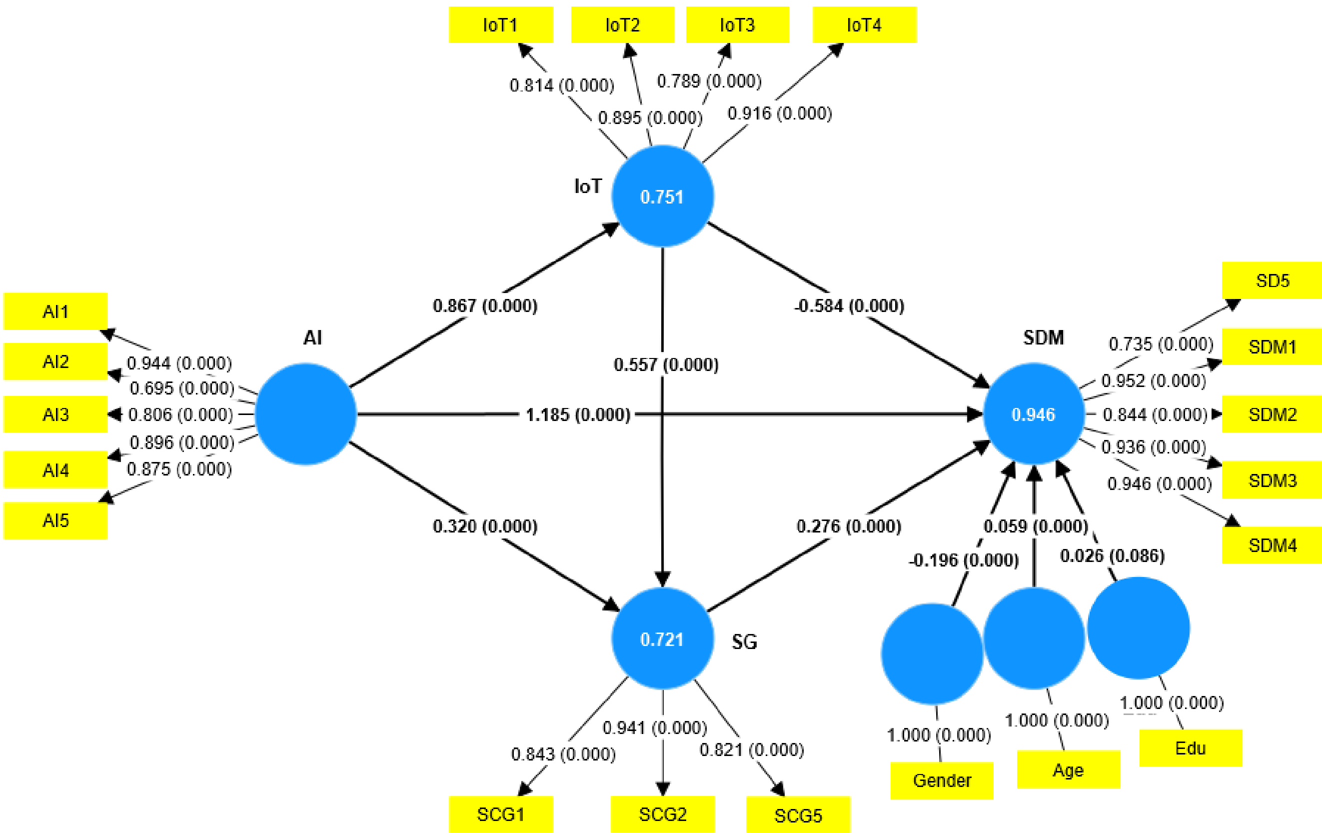

FIGURE 3. Structural equation modeling results.

($\beta = 0.429$; t = 7.243; $p < 0.01$); the proposed mediator in the model (the Internet of Things) also showed a positive link with smart governance ($\beta = 0.616$; t = 10.392; $p < 0.01$). Meanwhile, bootstrapping indicated that the confidence interval [0.462; 0.710] excluded zero, indicating that the Internet of Things significantly mediates the relationship between AI applications and smart governance, hence, supporting H9. Finally, Model 4 in Table 5 (AI → IoT → SG → SDM) demonstrates a positive relationship between AI and smart decision-making ($\beta = 1.367$; t = 45.111; $p < 0.01$), so the proposed mediating variable (the IoT) indicated a significant link with smart governance ($\beta = 0.616$; t = 10.392; $p < 0.01$). The multi-mediating variable (smart governance) illustrated a strong and significant positive relationship with smart decision-making ($\beta = 0.368$; t = 19.247; $p < 0.01$). Likewise, bootstrapping results showed the confidence interval [0.161; 0.295] outside of zero indicates the Internet of Things and smart governance significantly mediate the relationship between AI applications and smart decision-making [91], supporting H10 significantly. Given that all the evaluated direct relationships demonstrated statistical significance, the mediating associations were determined to reflect partial mediation. A summary of all hypotheses together with their results and factors of influence are given in Table 6.

These statistical and analytical outcomes by PLS-SEM provide adequate responses to our research questions and investigations of our hypotheses. Discussion of the results of our analyses, conclusions, and practical implications, with future research suggestions, is in Section V.

3) CONTROL VARIABLES

The PLS path model exhibited an amalgam of positive and negative effects that were statistically significant for various control variables, as indicated in Table 4. Specifically, there was a negative association between gender and AI ($\beta = -1.064^{**}$; t = 11.097; $p < 0.01$), the IoT ($\beta = -0.563^{**}$; t = 12.015; $p < 0.01$), smart governance ($\beta = -0.622^{*}$; t = 11.266; $p < 0.01$), and smart decision-making ($\beta = -0.181^{**}$; t = 5.265; $p < 0.01$). There was a positive correlation between age and the use of AI ($\beta = 0.243^{**}$; t = 5.391; $p < 0.01$), the IoT ($\beta = 0.238^{**}$; t = 14.382; $p < 0.01$), and smart decision-making ($\beta = 0.057^{**}$; t = 3.652; $p < 0.01$). Conversely, age showed a negative correlation with smart governance ($\beta = -0.168^{**}$; t = 7.864; $p < 0.01$). Finally, education exhibited a negative correlation with AI applications ($\beta = -0.201^{**}$; t = 6.534; $p < 0.01$), and a negative relationship with smart governance ($\beta = 0.049^{**}$; t = 2.321; $p < 0.05$) but revealed no association with the IoT

TABLE 7. Results comparison with previous research.

Effects	Relationships	Sectors	Literature
Direct Effect	Use of AI in Decision-making	Smart Cities	[4, 19, 25, 102]
		Literature Review	[103]
		Accounting & Auditing	[104]
		Medical & Medicine	[105]
		Governance	[106]
Mediating Effect	Social Innovation	Smart Cities	[19]
	Effectiveness and Discomfort	Human Behavior	[107]
	Technology Anxiety	Smart Cities	[25]
	Patient's Cognitive Engagement	Healthcare	[108]
	E-Governance	Smart Cities	[109]
Moderating Effect	consumer expertise	Marketing	[99]
	Internal Threats of IoT	Smart Cities	[25]
	Experience-based decision-making	Healthcare	[110]

($\beta = -0.011$; t = 0.498; p < 0.619) and the implementation of smart decision-making strategies ($\beta = 0.027$; t = 1.798; p < 0.072). The findings pertaining to the control variables are consistent with prior studies [19], [25], [64].

V. DISCUSSION

AI is becoming famous from advanced algorithms, big data, and improved storage and computing capacities. AI systems are enhanced with immersed digital system components, are more specific, and are having a profound effect on decision-making. Consequently, there is a surging demand for IT system social science researchers to understand and investigate the implication of artificial intelligence on decision-making so they can contribute to the practical success and theoretical development of AI applications [4]. Additionally, we cannot neglect understanding and investigating the indirect factors that can impact (positively or negatively) the association between AI and decision-making. This study intends to address this necessity by highlighting, analyzing, and investigating the critical factors in this research area, such as the Internet of Things and smart governance. Several previous scholars found a moderating impact from factors between AI and decision-making [98] and a mediating impact from factors between two constructs [19], [25], [99], so we inferred there are parallel-sequential multiple mediating factor impacts in order to investigate the smart decision-making process from using AI to govern a smart city. A total of 10 hypotheses were developed and then investigated by using PLS-SEM to achieve our desired outcomes and to provide generalizations for researchers. Table 7 presents a comprehensive comparison of the findings from prior research pertaining to the direct influence of AI applications on decision-making, the contextual effects of moderating variables, and the indirect mediating effects that exist between these two constructs.

In this study, we explicitly investigated the multiple factors that can impact the smart decision-making process in the context of developing countries. First, we investigated the direct relationship between AI on smart decision-making and found significance between both variables. Then, we introduced two mediating variables (the IoT and smart governance) between the independent and dependent variables. The findings from empirical analysis of the direct and indirect relationships among AI, the IoT, smart governance, and smart decision-making showed that AI applications have a strong, direct influence on smart decision-making, the IoT, and smart governance. Likewise, a strong direct impact from the IoT was found on smart governance and smart decision-making. Further findings elaborated on a strong direct effect from smart governance on smart decision-making. After investigating the direct relationships, this study examined the indirect effects of the IoT and smart governance. The outcome showed that the IoT has a substantial mediating role between AI and smart decision-making, that smart governance has a significant mediating impact between AI and smart decision-making, and that the IoT mediates the relationship between AI and smart governance positively. Finally, a significant multi-mediating impact from the IoT and smart governance was foud between AI and smart decision-making.

Governors of smart cities can utilize surveillance cameras, environmental sensors, charging stations, electronic billboards, Wi-Fi, and traffic management systems to collect, transform, and transfer data, and use them for decision-making. When there is a high level of AI utilization in a city, and the Internet of Things available to help govern, there is a greater likelihood that governance in the city will be better, and decisions for the public will be made smartly. The concern of this study is to investigate direct and indirect relationships between AI, the IoT, smart governance, and smart decision-making, and we proved these relationships with empirical evidence that all these hypothesized relationships exist. They were supported when investigated using PLS-SEM and regression analysis.

A. STUDY IMPLICATIONS

1) THEORETICAL IMPLICATIONS

This study has significant theoretical implications that enhance our comprehension of why, how, and when AI applying big data is significantly associated with smart decision-making in smart cities. Previous research by

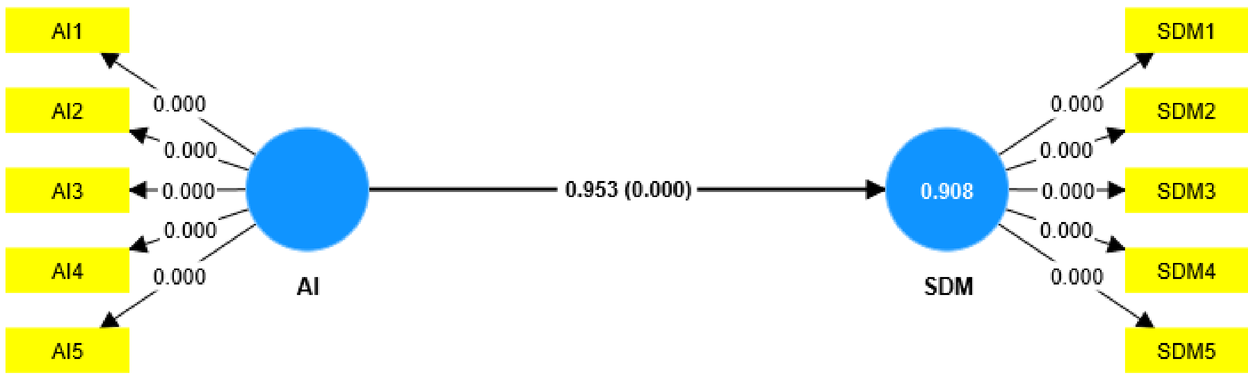

FIGURE 4. Direct effect of AI application on smart decision-making without including mediating variables.

Bokhari and Myeong [19] advanced the theoretical developments and pragmatic effectiveness of AI applications in smart cities, but it is essential to comprehend and examine the indirect aspects that may influence the positive or negative association between AI and smart decision-making. This study demonstrated that IoT systems and smart governance are critical mediatory structures, and it unlocks the black box interactions between AI and smart decision-making. Following traditional decision theory [100], our results demonstrate that AI applications significantly enhance both work and life and can strengthen smart decision-making. Nonetheless, IoT systems pertaining to their utilization may encourage city governors to provide smart services that enrich smart governance, thereby positively affecting their smart decision-making.

In today's digital age, when modern technologies include a huge spectrum of innovative services, this study expanded a holistic framework and empirically validated the associations between variables, resulting in an extensive but still emergent study examining the interaction between AI and smart decision-making in smart cities. Our study discovered that IoT systems can be used as a parameter in the correlation between AI and smart governance, in addition to the direct correlation between AI and smart decision-making. According to the findings of this study, IoT systems and smart governance not only mediate the interactions between independent and dependent variables, but they also mediate the relationship between AI applications and smart decision-making.

2) PRACTICAL IMPLICATIONS

We have purposefully taken a broad view of AI-based decision-making systems in this paper. The term *artificial intelligence* has evolved into a catch-all for a broad range of technologies that perform extremely challenging activities. This study has several implications for local city managers or smart governors. Information can be extracted from the instances identified, but we do not present a comprehensive overview of all AI applications in the smart city framework. As an illustration, our categorizations indicate that most of the current research on AI has focused on assisting humans with decision-making instead of replacing humans. City leaders can use categorization to learn about residents' opinions on government and AI acceptance. Our study was conducted in the private and public sectors of a South Asian country and suggests that city governors can benefit from our research in multiple ways. Small or rural cities may not see any impact from this study due to a lack of resources, technology, social inclusion, and political influence, among several other factors, but urban cities can obtain advantages. The main objective of this study is smart decision-making using AI, so we highlighted the factors that contribute positively, and significantly so local government managers can keep in mind these factors while making policies and decisions affecting the public. Sensors nowadays are important devices for data collection, and big data may be processed and used for decision-making in smart cities to provide inhabitants with a better quality of life and better services. Moreover, data collected by local government can be shared with entrepreneurs, businesses, and industries for the prosperity of society and all relevant stakeholders, including social innovationists who should be involved in a collaborative decision-making process by the city government, keeping in mind that they are the ones who will be affected directly or indirectly by such decisions.

B. STUDY LIMITATIONS AND FUTURE RESEARCH

Like several other empirical studies, this study possesses innate limitations that require careful consideration when interpreting, expanding upon, and applying the findings to more general contexts. Given that this study was conducted in South Korea (an Asian country), it is important to acknowledge that the characteristics of the participants analyzed may not necessarily generalize to people from other cultural backgrounds and to countries that are different from the aforementioned context. Therefore, it is crucial to conduct more research on the differences in social structures between countries or continents in order to address developments in e-governance.

First, one possible limitation is the small sample size from questionnaires (516). Although numerous previous studies had smaller samples, we believe the results might be different with a larger sample, but the data collected from the questionnaires is still sufficient to support the reliability and accuracy of the findings [110]. That was inevitable in our context, because the data were collected in South Korea, and most of the answers were collected online. However, this creates an opportunity for researchers to examine the perspectives of individuals from around the world. Improved outcomes can be produced by collecting data from multiple countries and investigating them for comparative analysis.

Second, although we constructed the questionnaire diligently and carefully to avoid social or nationalist pressure on the participants, it is possible that some of the participants felt some implied social or nationalist pressure to answer the questions in their country's favor because people like to show their own country is better. Future researchers can avoid this social desirability bias by constructing questions to be as unbiased, neutral, and non-threatening as possible to keep respondents comfortable and to get proper responses.

Third, this study was conducted in a developed country, and most of the respondents were well-educated. There is a possibility of variation in results for future researchers if the sample is collected from different economies. Most of the previous studies were conducted in advanced Western countries where annual income is high, people are highly educated, and technologies are implemented at higher levels. If the sample is collected from a low-education and low-income population, the results might be different.

Fourth, this study heavily depended on convenience sampling and the majority of respondents were young males, which limits age and gender in the generalizability of the findings. To avoid this limitation, researchers in future studies can employ a quota-based sampling method that employs a specific percentage of fixed age categories and by ensuring the sample group is equally male and female. Moreover, the relationship between the study variables can be clearly represented with a longitudinal research design.

Fifth, validity and reliability were evaluated with the help of novel statistical software (SmartPLS 4.0). This scientific technique tests the hypothesis with numbers. Conversely, a mixed-method approach could be employed to strengthen the findings and determine some other potential components in a government's smart decision-making procedure, in addition to the qualitative research of respondents' perceptions.

Sixth, this study adopted a cross-sectional design. The level of satisfaction among stakeholders can differ depending on their sustained interactions with a social group or changes in the contextual environment, which may include government support. The existing body of literature suggests that satisfaction is a result of expectations that have the potential to change over time. Future studies may explore the longitudinal implications of the aforementioned factors or alternative variables.

Seventh, the survey data were obtained from one particular source using a uniform methodology. As a result, respondents may be susceptible to bias. Additionally, it should be noted that the sample size was relatively small. While it is feasible to use PLS path modeling with small sample sizes, it is suggested that researchers replicate the results of this study by utilizing various sources of information and a more extensive sample.

Finally, this paper is optimistic about AI applications for smart decision-making by smart city governors, and a positive research design was developed. Some AI-enabled systems may have flaws due to biases, discrepancies, or an absence of sophistication in their applications.

VI. CONCLUSION

Compelled by the vibrant domain of AI and decision-making in smart cities, this study highlights key findings to improve the understanding of AI applications for smart decision-making. The explosive development of the AI-enabled IoT has resulted in certain inherent advantages; a proportion of such advantages are associated with IoT systems persistence resulting from effective network usage, the interconnection between the public and the government, and good governance. Aligned with the results of the research [74], the IoT must be built in a method that encourages smart governance, which will aid in smart decision-making. To utilize the advantages of AI and IoT systems for smart decision-making, city governments must have the trust to truly accept them. Consequently, smart-city decision-makers must take appropriate measures to implement such technologies in order to govern smartly. This comprehension is critical, not only for policymakers but also for promoting smart service provision and sustainability. Since AI has gained traction as an outcome of the application of big data, complex algorithms, and greater computational storage and power, artificial intelligence is getting widely implemented into regular service delivery and has a significant impact on smart decision-making.

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