

Retraction

Retracted: The Use of Artificial Intelligence for Smart Decision-Making in Smart Cities: A Moderated Mediated Model of Technology Anxiety and Internal Threats of IoT

Mathematical Problems in Engineering

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] A. Alloulbi, T. Öz, and A. Alzubi, "The Use of Artificial Intelligence for Smart Decision-Making in Smart Cities: A Moderated Mediated Model of Technology Anxiety and Internal Threats of IoT," *Mathematical Problems in Engineering*, vol. 2022, Article ID 6707431, 12 pages, 2022.

Research Article

The Use of Artificial Intelligence for Smart Decision-Making in Smart Cities: A Moderated Mediated Model of Technology Anxiety and Internal Threats of IoT

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With the rapid development of artificial intelligence (AI), AI for smart decision-making is attracting a lot of attention, but research on this topic in smart cities is not yet comprehensive. Thus, the current research aimed to examine the direct and indirect (via technology anxiety) relationships between artificial intelligence (AI), technology anxiety, and smart decision-making (SDM). The research article also examines the moderating role of internal threats of IoT on AI and technology anxiety and the relationship between AI and smart decision-making. 614 cross-sectional data gathered from participants from public and private sectors in Turkey were utilized to investigate the aforementioned relationships. The results indicated that AI had a positive influence on smart decision-making. AI contributes negatively to technology anxiety. Technology anxiety has a negative effect on smart decision-making. Technology anxiety partially mediated the direct effect of AI on smart decision-making. The results revealed that internal threats of IoT moderated the negative relationship between AI and artificial intelligence, such that the negative relationship is further strengthened when internal threats of IoT are high. The results also indicated that internal threats of IoT moderated the positive direct relationship between AI and smart decision-making, such that the positive relationship is weakened when internal threats of IoT are high. The findings present crucial practical implications for government and local authorities in building smart cities.

1. Introduction

The use of artificial intelligence (AI) has been claimed to provide transformational potential in different areas, ranging from smart cities, its influence on governance, and innovative discipline, and even promote human capabilities [1–4]. With the advancement of technology, AI has taken a significant leap becoming an essential part of everyday life [5]. From this standpoint, AI and its transformational potential had become hot topic for discussion in both practice and literature in the modern era [1, 6]. In both government and private sectors, data generation through AI is possible in exploring innovative ways to comprehend our world. With the rapid advancement of big data technologies and their availability, AI is being revitalized while enabling informed

decision [7]. AI promotes smart cities' decision-making because SDM involves the systematic technique to data collection and its application of logical decision-making methods rather than generalizing from experience, intuition, or the use of trial and error [8].

“Smart cities” has been defined in various ways by several scholars because it is a multifaceted concept. Nevertheless, the necessary requirement for smart cities is to promote quality of life and attain sustainable development using AI and information and communication technology (ICT) [9]. Based on this, Atlam et al. [10] defined a smart city with respect to the technology aspect as “a technologically interconnected city” or Internet of things (IoT) utilizing big data to attain intelligent and efficient handling of cities resources. Albino et al. [11] research regarding SDM in

smart cities through big data conceptualized three-dimensional layers distinguishing feature of a smart city, namely, instrumentation, interconnection, and intelligence. Smart cities in the implementation stage use AI and IoT for the purpose of data collection through the usage of sensors, meters, cameras, and social media for fast feedback. The data gathered through the use of AI, IoT, and the above-mentioned sources are then incorporated and transformed into even-related message in the interconnection stage to produce a deeper understanding for smart city decision-making. Consequently, the collected information through the data is then projected to comprehend the city's needs, demands, requirements, and needed policies, thus promoting well-rounded and smart decision-making [11, 12].

With smart cities impacting various areas of human's life, AI and IoT system may be subjected to information attacks, leading to security problems such as user data disclosure. Based on this, Roman et al. [13] argued that one of the main issues that must be overcome concerning IoT is security. People's perception and attitude are crucial determinants of success for any smart services [14]. The social cognitive theory postulates that anxiety is a crucial determining factor in behavioral intentions [15]. Technology anxiety is a major factor influencing the use of self-service technology [16]. Technology anxiety relates to "the fear, apprehension, and hope that individuals feel when considering use or actually using certain technology" [16]. This reenergizes the idea that technology anxiety could play a crucial role in the relationship between AI and SDM. Consequently, technology anxiety is introduced as a mediator in the relationship between AI and SDM.

Prior studies have acknowledged and discussed the impact of AI on smart decision-making process. However, several factors can influence decision-making in smart cities [17]. Furthermore, our understanding of the precise usage of AI on smart decision-making in smart cities is still limited, especially in Turkey. From a research point of view and to the best of our knowledge, no study has examined the four constructs in this study simultaneously. Therefore, in furthering the existing literature, this study aimed to test a moderated mediation model where both the direct and indirect relationships between the uses of AI in smart decision-making are mediated by technology anxiety and moderated by internal threats of IoT (Figure 1).

1.1. Theoretical Background and Hypotheses

1.1.1. AI. In the public sector, e.g., municipalities, Mikalef et al. [18] noted that the deployment levels of AI are still at the early stage. Leveraging AI in such context is subjected to variety of various forces and is hampered by factors such as legal, political, and policy challenges [3]. Studies related to AI in the public organization have attracted limited attention, although lately there has been a rise in AI-related research and technical reports (see [4, 19, 20]). These studies emphasized the importance of the application of AI in the public organizations across various branches of governance, indicating that the massive potential of AI is being diminished by organizational, technical, and policy difficulties.

Prior studies have substantiated the crucial impact of AI in rational decision-making procedures, facilitating a high-quality life and making a city smart in practice. AI-enabled governance has been characterized as enabler of collaboration among cities to establish smart services that could have been impossible for a single city to create [21]. AI-enabled governance in smart cities promotes collection of data through sensors and other sources in enhancing urban safety governance [22]. Most recently, the South Korean government used AI in response to the coronavirus pandemic to provide an exchange of information to its citizens, helping them in comprehending the situation and applying government-released safety measures [23].

AI using information technology is the cornerstone of smart cities [24]. As the world population grows and increases urbanization, AI technologies are increasingly being used to improve quality of life: smart traffic [25], intelligent information management [26], and smart health care [27]. Such evolution typically consists of various AI approaches that are widely adopted by city's decision-makers who establish the governing system [28]. AI through intelligent information processing or data analysis can improve data cleaning, data collection, and storage to gain more insight from generated data. Such a crucial attribute is a vital element of automated learning and decision-making process by complex mathematical depiction of the issues.

In government, AI can help to enhance power structure through smart decisions by providing new and smart services. Such qualities in decision-making process can offer solution to common mistakes in administrative decision-making procedures such as improper forecast of administrative tasks [1].

1.1.2. Artificial Intelligence and Decision-Making in Smart Cities. AI has well been documented to aid decision-making in several disciplines ranging from private and public organizations to smart cities. AI has been reported to be very useful in reinventing business models and ecosystems, thus promoting decision-making [1]. The usefulness of new generation of AI systems to forecast strong-impact weather is widening human's ability to explore huge amount of data in order to gain insights and serves as a proper guide for analysts and decision-makers [29]. Several private organizations and governmental organizations across the world provide open datasets online that can be unutilized for data analysis and decision-making. From this standpoint, Marr [30] argued that the actual value of big data is not in the huge volume of data but in the advancement of new generation of AI systems such as machine learning ability to analyze complex and massive dataset beyond anything we could ever do before. Such evolution would provide rich insights for decision-making.

The building of a smart city is a complex, systematic, and extremely advanced integrated project that includes sensing devices, information collection, and monitoring of infrastructure to enhance decision-making [31]. Furthermore, prior studies pointed out that processing and the interpretation of big data through AI are a huge step aimed at

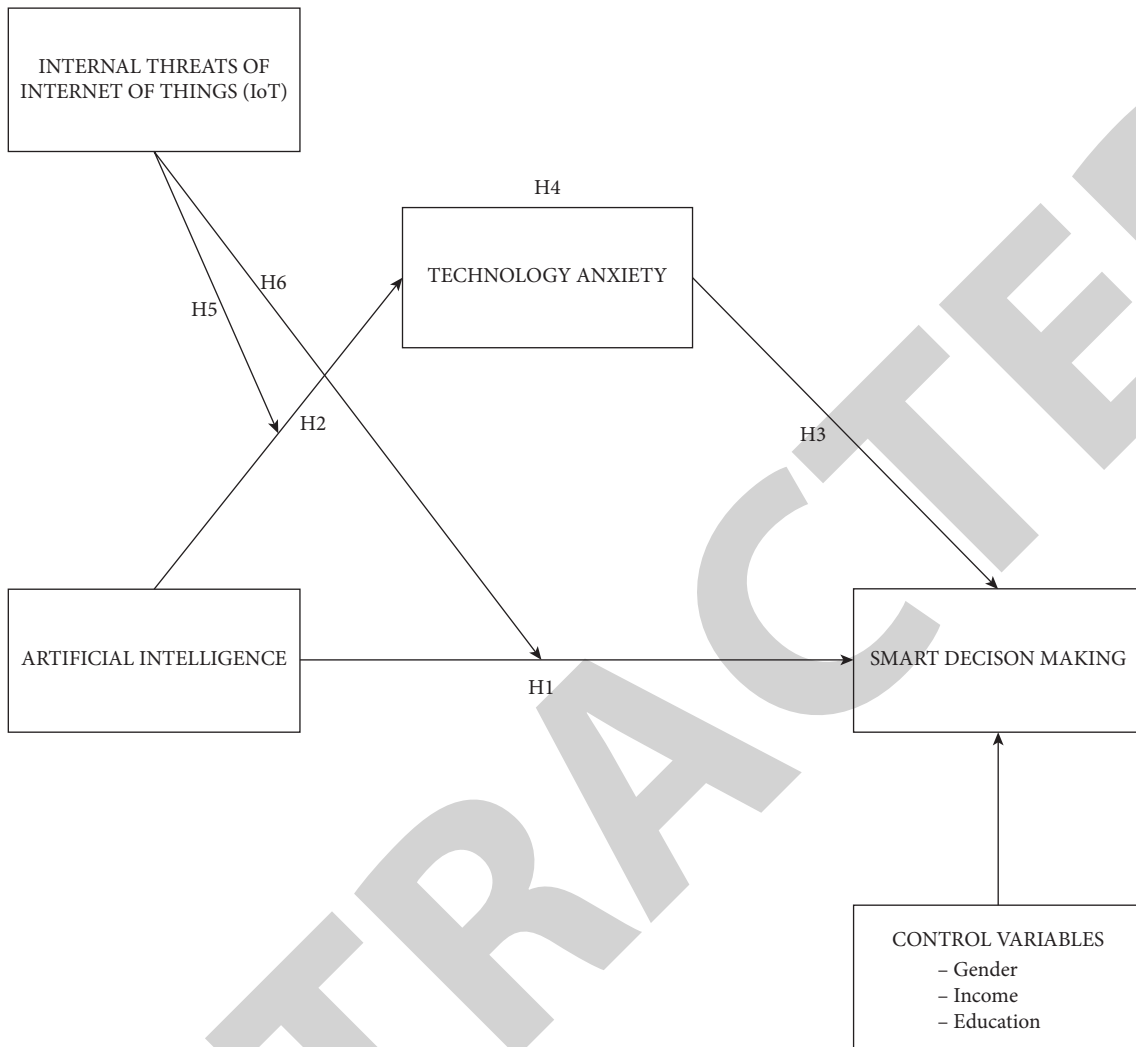


FIGURE 1: Conceptual model.

improving decision-making in smart cities [8, 32]. Digital ideas associated with AI technologies are enabling cities to become smart as the push for modern concept of “smart” is being made increasingly possible through the collection of real-time data and interpretation of such data to gain insight into how cities transform, adjust, and react to diverse environments [32]. Thus, we hypothesized that

H1: artificial intelligence using big data is positively related to SDM in smart cities

1.1.3. AI and Technology Anxiety. With the accelerated growth of AI, people have slowly begun to show concerns about AI [33, 34]. From this standpoint, numerous studies have indicated that AI technologies had overtaken humans in several aspects; AI performs substantially better than humans in the game of Go [35] and defeated 99.8% of human players in StarCraft [36]. Additionally, several research and professional assessments have also stimulated anxiety. About 400 to 800 million jobs were forecasted by the McKinsey Global Institute to be replaced by AI by 2030 [37].

A large number of expert opinions in addition to facts indicated that technology anxiety through the use of AI has become a global phenomenon that will highly affect people’s life paths, future study, and work [33, 38]. Furthermore, AI has been suggested to create technology anxiety and a succession of other social issues in smart cities [39]. Based on the above evidence and reasoning, we hypothesized that

H2: AI contributes negatively to technology anxiety in smart cities

1.1.4. AI, Technology Anxiety, and SDM. A smart city utilizes information system-centric procedures through intelligent usage of ICT within an interactive infrastructure to offer its citizen innovative and upgraded amenities, therefore influencing the quality of life of the people [40]. Technology has changed the way individuals work, the balance between personal and work-life [41]. However, in several fields of modern life, individuals are anxious about the possible existence of superintelligent technologies and the anxiety tends to be growing more [42]. From this standpoint,

technology anxiety plays a crucial role in the endorsement of various smart services [14] and thus smart decision-making.

As AI becomes more and more important in public organizations, the question of how AI should be integrated into decision-making process is becoming increasingly more important. In the context of technology adoption, technology context or technology anxiety has been suggested to play a crucial role in the adoption of disruptive technologies, for example, big data [43] and cloud computing [44]. This offers an essential orientation point for research of AI in public organizations. Furthermore, the technology context describes the impacts of perceptions of technology. The qualitative study of Schaefer et al. [45] pointed out some of the challenges pertaining to AI tool adoption via interviews of municipal employees in Germany. The study highlighted how self-service systems are constantly optimizing and evolving themselves, which indeed can help municipality employees to streamline and automate processes, thus smart decision-making. However, AI anxiety or technology anxiety in particular entails the independent self-evolution of machine and the iteration speed of AI is a lot quicker compared with that of humans [34]. Additionally, AI can make independent decisions and operate autonomously of humans [46], which can rest in unpredictable harm [47]. For this reason, people with high technology anxiety are more unlikely to use it [16], thus influencing their smart decision-making. As argued by Little et al. [48], many direct relationships rely on contextual factors, so in this study we examine the role of technology anxiety on the direct relationship. In accordance with the above empirical evidence and argument, we posit that

H3: technology anxiety negatively influences smart decision-making in smart cities

H4: technology anxiety plays a mediating role between AI using big data and smart decision-making

1.1.5. Internal Threats of IoT as a Moderator. IoT relates to the network of interconnected physical devices across the globe that are equipped with connectivity to collect gather, transfer, and share data [26, 49]. IoT development is important because it helps cities, buildings, and management services make smarter plans for change through ICT [50]. Many private companies have increased the number of remote and sensor monitors used in managing an organization's environment, which encouraged the government to adopt new technologies in smart cities to promote energy efficiency, traffic congestion reduction, and improve water and air quality. The IoT devices such as electronic communications, social networks, machinery, digital hearing aid, Fitbit, or GPS create streams of data by connecting and monitoring people [51–53]. However, these devices or systems commonly make use of wireless communication, sometimes with open characteristics that bring convenience to users, threatening the system security and users' privacy [54]. IoT encounters challenges such as internal threats due to security challenges of the systems because they can be easily hijacked by cybercriminals [54]. From this standpoint, prior research has indicated that technology anxiety, especially within the context of computer-related system and information

TABLE 1: Demographic information.

Characteristics ($n = 614$)	n	Percentage (%)
Gender		
Male	338	63.2
Female	226	36.8
Income (Turkish Lira)		
Less than 5000	165	26.9
5000–10000	195	31.8
10001–15000	130	21.2
15001–20000	95	15.5
20001 and above	29	4.7
Education		
High school	123	20.1
Vocational degree	260	42.3
Bachelor degree	147	23.9
Master degree and above	84	13.7
Marital status		
Married	321	52.3
Single	207	33.7
Divorced	80	13.0
Widowed	6	1.0

services, is quite common [55, 56]. Consequently, individuals with greater concerns regarding internal threats of IoT are more likely to stick to the services they are used to, rather than switching to some new generation AI technologies. Thus, we argue that high internal threats from IoT can further strengthen the negative relationship between AI and technology anxiety.

Roman et al. [13] suggested that privacy and security concerns are the major determinants that will impact the adoption of IoT in the development of a smart city. The study further suggested that should the problems be too complex and the advantages too little, individuals may stick with the traditional services they are accustomed to. Furthermore, the main idea behind IoT is global connectivity (“access anyone”) and accessibility (“access anyhow, anytime”), and such rationale makes the threats that can affect IoT systems enormous [57, 58]. Such threats regarding how IoT systems work have been suggested to impact decision-making process in adopting smart services [59]. Together, we expect that internal threats from IoT may mitigate the influence of artificial intelligence on SDM in smart cities. Thus, we hypothesize the following:

H5: internal threats of IoT moderate the negative relationship between AI using big data and technological anxiety, such that the negative relationship is strengthened when internal threats of IoT are high.

H6: internal threats of IoT moderate the positive relationship between AI using big data and SDM, such that the positive relationship is weakened when internal threats of IoT are high.

2. Methods

2.1. Sample and Procedures. The participants of this study were Turkish adults between the ages of 21 and 65 years. A questionnaire survey was sent electronically through email containing the link to survey to the targeted audience to achieve

the study's objectives. The participants were asked to complete the questionnaires and forward it to us via the email. All the measurement items adopted in the current research were primarily in English; however, our sample is from Turkey. Hence, with the help of two different professional experts, the items were translated into Turkish and then translated back into English to ensure double-check for precision. A total number of 723 questionnaires were distributed; 614 valid responses were recovered with a response rate of 84.92%. The participants were requested to give their opinions regarding the use of AI in smart cities, their perceptions about technology anxiety, and internal threats of IoT associated with public services and smart decision-making. All the constructs in the current research were rated on a 5-point Likert scale (where 1 = strongly disagree to 5 = strongly agree).

The demographic information is illustrated in Table 1. 338 (63.2%) of the participants were males, and 226 (36.8%) were females. 449 (73.2%) earn above 5,000 Turkish Lira, and a large proportion of the participants (491 (79.9%)) had at least vocational degree. In terms of marital status, the majority of the participants were married (321 (52.3%)).

2.2. Measurement Items. Artificial intelligence was measured using 5 items adopted from [60, 61]. The items were worded to extract participants' perceptions about AI trustworthiness and the influence on the society.

Technology anxiety was measured using 5 items from [14]. It measures participants' perceptions of smart services in smart cities.

Internal threats of IoT were measured using 3 items from [62]. A sample item is "most IoT devices operate unattended by humans; thus, it is easy for an attacker to physically gain access to them."

Smart decision-making was measured using 5 items from [63] regarding the use of new technology for decision-making.

2.3. Control Variables. Gender, income, and education were controlled in this study.

2.4. Statistical Methods. Data collected were analyzed using SPSS 28 and AMOS 26 software. In particular, AMOS 26 was used for confirmatory factor analysis to estimate the measurement model of all the variables in this study. SPSS 28 was used for descriptive statistics, common method bias, Pearson's correlation analysis, and PROCESS (plug-in) compiled by Hayes. PROCESS models 4 and 8 were chosen to examine the mediation model and moderated mediation model, respectively [64]. 5000 bootstrap resamples with confidence interval (CI) of 95%; that is, where the 95% CI excludes zero indicates a significant conditional indirect effect.

3. Results

3.1. Common Method Variance. Data were collected via self-report measure. To rule out the possibility of common method variance (CMV) associated with self-report method,

the respondents were told to rate the items anonymously. Furthermore, the Harman single factor test was adopted. The results showed that the first component for variance interpretation rate accounted for 23.61%; this is below the critical threshold of 50%, suggesting that CMV was not a major concern in this research [65]. In addition, the variance inflation factor (VIF) results for correlation between our study's constructs were below 3, implying that there are no substantial collinearity problems in the results [66].

3.2. Measurement Model. Testing for data distribution, Lei and Lomax [67] indicated that skewness and kurtosis indexes should not surpass [2.3]. As demonstrated in Table 2, the skewness values are from 0.027 to 1.235 and kurtosis values from 0.013 to 1.553. Thus, the measured items are within the acceptable thresholds, indicating that the collected data are normally distributed.

Next, we test the reliability and validity of the measurement items. The factor loadings for all items were found to be higher than 0.6. To fulfill convergent validity, the average variance extracted (AVE) of each variable is estimated [68]. The minimum threshold for AVE should be 0.5 [69]. To estimate composite reliability, the construct reliability (CR) was measured for each variable. Its lowest threshold should be 0.7 [70]. The results as illustrated in Table 2 revealed that all factor loading ranged from 0.602 to 0.989, AVE ranged from 0.611 to 0.799, and CR ranged from 0.871 to 0.952, thus suggesting that items are appropriate, and the variables are reliable and consistent.

Fornell and Larcker [68] recommended that for discriminant validity, the square root of each AVE is larger than the surrounding correlations, and then, discriminant validity is established. The results showed that the square of AVEs (illustrated in bold parenthesis) is larger than the surrounding correlation, indicating evidence of discriminant validity as shown in Table 3.

Table 4 shows the confirmatory factor analysis (CFA) of the adopted model (research model). The model fit indices were estimated by several statistics: IFI, CFI, NFI, RMR, TLI, and RMSEA. IFI and TLI should be higher than 0.8, CFI should be higher than 0.9, RMR should be higher than 0.1, and RMSEA should be lower than 0.08 [71]. All fall within the recommended thresholds, indicating the research model, shows an acceptable fit with the data collected.

3.3. Testing for Mediation Model. To examine hypotheses, H1, H2, H3, and H4, the PROCESS macro-model 4 compiled by Hayes was used. The relationship between AI and SDM was supported predicted in H1 ($\beta = 0.367$, $p = 0.000$, 95% CI exclude zero, 0.276 to 0.458) as illustrated in Table 5. This result revealed that AI using big data has a positive significant effect on SDM. The relationship between artificial intelligence and technology anxiety was validated as predicted in H2 ($\beta = -0.799$, $p = 0.000$, 95% CI = -0.276, -0.113). The results revealed that artificial intelligence has a negative significant effect on technology anxiety. Also, there was a negative significant relationship

TABLE 2: Reliability and validity assessments.

Constructs	Measurement items	Factor loading (λ)	Normal distribution	
			Skewness	Kurtosis
Artificial intelligence	(α = 0.953; CR = 0.952; AVE = 0.799)			
	AI1	0.989	-0.467	-1.212
	AI2	0.960	-0.489	-1.371
	AI3	0.800	-0.897	-0.556
	AI4	0.840	-0.825	-0.795
	AI5	0.860	-0.113	-1.505
Technology anxiety	(α = 0.907; CR = 0.889; AVE = 0.621)			
	TA1	0.980	-0.381	-1.410
	TA2	0.710	-1.089	0.013
	TA3	0.770	-0.015	-1.549
	TA4	0.640	-0.895	-0.248
	TA5	0.790	-0.008	-1.545
Smart decision-making	(α = 0.813 CR = 0.871; AVE = 0.611)			
	SDM1	0.900	0.107	-0.812
	SDM2	0.690	-0.275	-1.370
	SDM3	0.691	0.484	-1.416
	SDM4	0.680	0.027	-1.458
	SDM5	0.790	0.036	-1.553
Internal threat of Internet of things	(α = 0.869; CR = 0.873; AVE = 0.688)			
	IOT1	0.602	-1.235	1.042
	IOT2	0.980	-0.665	-0.920
	IOT3	0.950	-0.700	-0.812

Note. (1) AI = artificial intelligence; TA = technology anxiety; SDM = smart decision-making; IOT = internal threat of Internet of things; (2) AVE = average variance extracted; CR = composite reliability; α = Cronbach's alpha.

TABLE 3: Descriptive statistics, Pearson's correlation matrix, and discriminant validity.

Construct	M	SD	AI	TA	SDM	IOT	Gender	Income	Education
AI	3.711	1.409	0.799						
TA	3.490	1.312	0.649**	0.621					
SDM	3.246	1.304	0.619**	0.522**	0.611				
IOT	2.866	1.990	0.538**	0.602**	0.591**	0.688			
Gender	1.370	0.483	0.662**	0.612**	0.566**	0.611**	—		
Income	2.394	1.171	0.544**	0.622**	0.540**	0.569**	0.573**	—	
Education	2.313	0.944	0.883**	0.827**	0.788**	0.622**	0.571**	0.608**	—

Note. (1) M = mean; SD = standard deviation; (2) correlation is significant at ** $p < 0.01$ (two-tailed); (4) boldface in parentheses indicates that the square root of AVEs is greater than the off-diagonal correlations.

TABLE 4: Model fit statistics.

Goodness-of-fit index	Acceptable limit	Model value
CMIN/DF	<3 excellent fit	1312.759/633 2.073
IFI	>0.9	0.941
CFI	>0.9	0.939
NFI	>0.9	0.900
RMR	>0.10	0.129
TLI	>0.9	0.937
RMSEA	<0.08	0.049

between technology anxiety and smart decision-making ($\beta = -0.322$, $p = 0.000$, 95% CI = -0.246 , -0.099).

With H1, H2, and H3 all being supported, for mediation analysis, 5000 bootstrapping was used. The bootstrap technique has become the accepted method for mediation analysis because of its ease and accuracy (see Hayes [72]). The distinction behind bootstrapping is the

use of a form of resamples of the data available to make inference and gain deep insight into the underlying population [73]. Hence, to provide the most reliable result for mediation analysis, a bootstrap resamples of 5000 were used in this study. The results revealed that there was a significant negative indirect relationship between artificial intelligence and smart decision-making via technology anxiety ($\beta = -0.293$, 95% CI = -0.203 , -0.101), and the confidence interval excludes zero. Therefore, hypothesis H4 was validated.

3.4. Testing for Moderation Model. To examine the moderating role of internal threats of IoT in the relationship between artificial intelligence and technology anxiety (H5) and the relationship between AI and SDM (H6), PROCESS macro (model 8) was utilized with gender, income, and education confounded for as covariates. The moderated mediation analysis is demonstrated in Table 6.

TABLE 5: Testing for direct and mediation effects.

Mediation results: technology anxiety partially mediates the relationship between artificial intelligence and smart decision-making (PROCESS model 4, 95% CI)
 Bootstrap 95% CI

	β	SE	t	p	LLCI	ULCI	R^2
Model 1: mediator variable model	Outcome: TA						
Artificial intelligence	-0.799	-0.016	-9.827	0.000	-0.276	-0.113	0.413
Model 2: outcome variable model smart decision-making							
Technology anxiety	-0.322	-0.041	-7.803	0.000	-0.246	-0.099	0.571
Artificial intelligence	0.367	0.047	7.880	0.000	0.276	0.458	
Bootstrapped results for the indirect effect (the indirect effect of AI on SDM via TA)	-0.293	0.048			-0.203	-0.101	

Note. $n = 614$; bootstrap resample = 5000; LLCI = lower level of confidence interval; ULCI = upper level of confidence interval.

TABLE 6: Testing for moderated mediation: internal threat of Internet of things moderated the direct and indirect relationship between artificial intelligence and smart decision-making (model 8, 95% CI).

Bootstrap 95% CI

	β	SE	t	p	LLCI	ULCI	R^2
Model 1: mediator variable model	Outcome: technological anxiety						
Artificial intelligence	-0.752	-0.028	-26.465	0.000	-0.696	-0.407	0.418
Internal threats of Internet of things	-0.119	-0.037	3.245	0.001	-0.087	-0.016	
Artificial intelligence X internal threats of Internet of things (interaction)	-0.066	0.016	-4.244	0.000	-0.136	-0.097	
Co: gender	-0.606	0.088	-6.912	0.000	-0.778	-0.434	
Co: income	0.314	0.029	10.598	0.000	0.256	0.372	
Co: education	0.244	0.063	3.518	0.001	0.108	0.379	
<i>The conditional direct effect of artificial intelligence on technology anxiety</i>							
Internal threats of Internet of things (-1SD)	0.665	0.049	13.418	0.451	-0.210	0.411	
Internal threats of Internet of things (+1SD)	-0.741	-0.042	-17.864	0.000	-0.068	-0.167	
Model 2: dependent variable model-dependent: smart decision-making							
Artificial intelligence	0.149	0.021	4.188	0.001	0.249	0.330	0.255
Technology anxiety	-0.314	-0.045	-6.923	0.000	-0.425	-0.201	
Internal threats of Internet of things	-0.488	-0.046	-10.516	0.001	-0.597	-0.379	
Artificial intelligence X internal threats of Internet of things (interaction)	0.089	0.055	2.700	0.001	0.108	0.258	
Co: gender	-0.538	0.102	-5.297	0.000	-0.737	-0.339	
Co: income	-0.137	0.036	-3.802	0.000	-0.208	-0.066	
Co: education	0.673	0.078	8.622	0.000	0.520	0.827	
<i>The conditional direct effect of AI on SDM</i>							
Internal threats of Internet of things (-1SD)	0.248	0.057	4.334	0.001	0.360	0.535	
Internal threats of Internet of things (+1SD)	0.051	0.063	1.816	0.001	0.175	0.372	
<i>Bootstrapped results for indirect effect (via technology anxiety)</i>							
Index of moderated mediation	0.020	0.006			0.010	0.032	
<i>The conditional indirect effect of artificial intelligence on smart decision-making (via technology anxiety)</i>							
Internal threats of Internet of things (-1SD)	-0.249	0.051			-0.125	-0.091	
Internal threats of Internet of things (+1SD)	-0.205	0.044			-0.101	-0.083	

Note. $n = 614$; bootstrap resample = 5000; LLCI = lower level of confidence interval; ULCI = upper level of confidence interval; Co = control variable.

The results showed that after confounding for demographic covariates, the effect of the interaction term between AI using big data and internal threats of IoT on technology anxiety was significant ($\beta = -0.066$, $p \leq 0.000$), and this provides support for H5 indicating that internal threats of IoT moderated the negative relationship between AI using big data and technology anxiety. The significant effect of the interaction was further investigated through simple slope analysis. The interactions were plotted at +1 and -1 SD from the mean of internal threats of IoT (demonstrated in Figure 2). We constructed a simple slope to check the strength of the relationship between AI using big data and technology anxiety at high and low levels of internal threats of IoT. The

results of the conditional direct effect of AI on technology showed that the negative relationship was stronger when internal threats of IoT were high ($\beta = -0.741$, $p \leq 0.000$), while the relationship was not statistically significant ($\beta = -0.665$, $p \geq 0.05$) at low level of internal threats of IoT, therefore further validating H5.

The results also revealed that the interaction effect of AI using big data and internal threats of IoT on SDM was significant ($\beta = -0.089$, $p \leq 0.001$), indicating that internal threats of IoT moderate the positive relationship between AI using big data and SDM. The interactions were plotted at +1 and -1 SD from the mean of internal threats of IoT (demonstrated in Figure 3). A simple slope analysis was

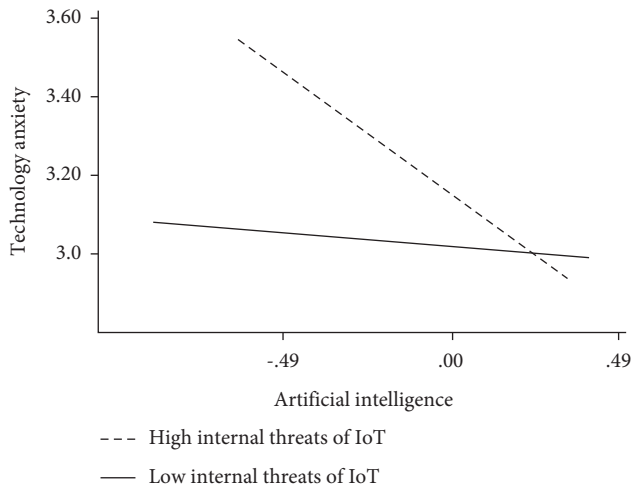


FIGURE 2: Association between AI and technology anxiety at different levels of internal threats of IoT: (1) low internal threats of IoT (1 SD below the mean) and (2) high internal threats of IoT (1 SD above the mean).

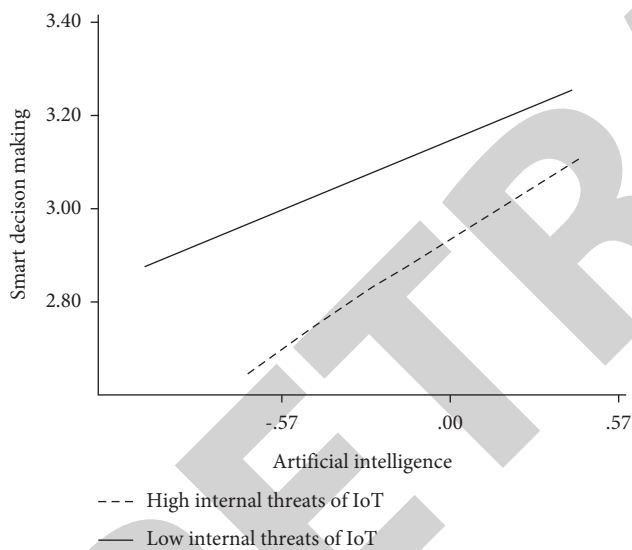


FIGURE 3: Association between AI and SDM at different levels of internal threats of IoT: (1) low internal threats of IoT (1 SD below the mean) and (2) high internal threats of IoT (1 SD above the mean).

constructed to examine the strength of the relationship between AI using big data on SDM at high and low levels of internal threats of IoT. The results of the conditional direct effect indicated that the relationship was stronger ($\beta = 0.205$, $p < 0.001$) when internal threats of IoT were low, while the relationship was weak ($\beta = 0.051$, $p \leq 0.001$) at high level of internal threats of IoT, therefore validating hypothesis 6.

Moreover, the results of the conditional indirect showed that internal threats of IoT moderated the indirect relationship (through technology anxiety) between AI using big data and SDM (bootstrapped estimate = 0.023, bias-corrected CI = 0.010 to 0.032). As illustrated in Table 6, the two

conditional indirect effects were statistically significant, plus bootstrap (confidence intervals) supported the results.

Finally, the results supported a moderated mediated model where technology anxiety is the partial mediator of AI using big data on smart decision-making.

4. Discussion

Based on the sample collected in Turkey, this study investigated a moderated mediation model and uncovered the underlying mechanism in the relationships between artificial intelligence using big data and SDM in the Turkish context. First, the results revealed that AI using big data has a positive impact on SDM in smart cities. This result aligns with the prior studies of [17, 32]. The consistencies of this pattern of result could suggest that AI technologies integrated with big data, complex algorithms, large storage, and processing capacity are influencing decision-making in smart cities. Second, AI was revealed to be a determinant of technology anxiety. This result aligns with Amodei [39] and supports the conclusions of [33, 38]. This particular result revealed that technology anxiety contributes negatively to technology in smart cities. Third, technology anxiety was found to be a significant and negative determinant of smart decision-making. This result provides empirical support for Meuter et al. [16], who suggested that the high level of technological anxiety will influence people's smart decision-making, by discouraging them not to use smart services in smart cities. Fourth, technology anxiety partially mediated the relationship between AI using big data and SDM.

Fifth, internal threats of IoT moderated the negative relationship between artificial intelligence and technological anxiety, such that the negative relationship is further enhanced when internal threats of IoT are high. Finally, the results showed that internal threats of IoT moderated the positive relationship between AI using big data and SDM, such that the positive relationship was weakened when internal threats of IoT were high.

4.1. Theoretical Implications. This study provides important theoretical implications. This study promotes our understanding of why and when artificial intelligence using big data is positively related to smart decision-making in smart cities. Bokhari and Myeong [17] made a research call that for theoretical advancement and practical success of AI applications in smart cities, it is crucial to recognize and investigate the indirect factors that may affect the good or adversarial relationship between AI and decision-making. Particularly, this research established that technology anxiety is a crucial intervening mechanism and opens up the black box for the relationship between AI and smart decision-making. Based on social cognitive theory [15] and self-service technology (SST) usage [16], our findings suggest that using AI technologies to improve both life and work in a substantial way may enrich smart decision-making; however, the anxiety related to its use can discourage people from using smart services, thus negatively influencing their smart making decision.

In the present era where sophisticated technologies offer a wide array of novel services, this study constructs a comprehensive model and empirically tested the relationships among the constructs leading to a substantial as-yet nascent study investigating the connection between AI and SDM in the smart city space. Our study revealed the internal threats of IoT as a boundary condition in the relationship between AI and technology anxiety, together with the direct relationship between AI and smart decision-making. The outcome of the current study indicated that the incongruence between interests in AI and users with high internal threats of IoT can impact the extent to which they make use of AI technologies, thus explaining the variation in the users' attitude regarding AI technologies and their smart decision-making. The difference in perspectives between interests in AI systems and users with high internal threats of IoT can be more ardent such that it further strengthens the negative influence of AI on technology anxiety and weakens the positive strength of the direct relationship.

In summary, our findings suggest that based on the levels of internal threats of IoT, users may show different levels of interests in AI technologies and therefore varying levels of AI impact on technology anxiety, and their smart decision-making can be observed. Based on this, this study presents a nuanced explanation by theorizing and presenting evidence that internal threats of IoT act as a boundary condition in the relationship between AI and SDM, therefore significantly extending the existing literature in AI and smart decision-making in smart cities research.

4.2. Practical Implications. The findings of the current research present important practical implications for decision-makers such as government and municipalities from a policy-making standpoint. It is important that government, local authorities, and technology providers create social awareness campaign that can encourage users that artificial intelligence applications, systems, and services respect data privacy and transparent and value individuals' choices. The decision-makers should understand the mental model of users regarding smart services that are not the same, thus must offer advanced personalization options. This can be achieved by simplifying the interfaces to facilitate a condition where smart service users feel no technology anxiety. By doing this, users would be encouraged to adopt smart services to improve their quality of life and thus smart decision-making.

Depending on the levels of internal threats of IoT, users may show different levels of interests in using smart services, and hence, we may experience different levels of AI system impact on technology anxiety and their smart decision-making. Understanding the crucial role of internal threats of IoT is particularly important, as this can help government and local authorities in designing social awareness campaign that is aimed at promoting users' adoption of smart services.

As stated by prior research that the major challenges in adoption and implementation of smart city applications are privacy and security issues [54, 74], it is important for government and local authorities to upgrade and fortify the

security system used in protecting smart service. Such action would reassure users they are protected from privacy and security breach.

5. Conclusion

Encouraged by the dynamic field of AI and decision-making in smart cities research, this research article presents important findings to better the comprehension of users' attitudes and perceptions of AI systems for smart decision-making. The rapid growth of IoT has come with some associated threats; a number of these threats are attributed to IoT device vulnerabilities arising from inappropriate use of system resources and cybercrime by hackers. Consistent with the findings of this study, it is important that IoT is constructed in a way that promotes safe and easy usage control. Users need confidence in order to fully embrace AI systems for smart decision-making to enjoy their benefits and avoid privacy and security risks. Therefore, decision-makers in smart cities should take the necessary steps to avoid such threats. This can be achieved by dealing with IoT devices' vulnerabilities through a smooth policy implementation process supported by strong procedures. Such understanding is not just crucial from policy-making perspective but also to promote smart services adoption and sustainability. As AI has gained popularity due to the use of big data, advanced algorithms, and enhanced processing storage and power, AI is increasingly being incorporated into our everyday life and substantially influences SDM. The results presented in this research significantly advance the comprehension of AI technologies and decision-making in both theory and practice [2].

5.1. Limitation and Future Research Direction. The present article offers some limitations that future studies can take advantage of. First, the sample used in the current research was constrained to Turkey; therefore, generalization to other nations is needed in future research. A cross-national survey can also be conducted by adopting the model in this study. Second, longitudinal research design is encouraged to make causal inferences. Third, limited research exists from users' perspective regarding intervening mechanisms in the association between AI systems and decision-making in smart cities research; therefore, future study could benefit by examining the work-life interface in the relationship. Iyiola and Rjoub [75] reported that trust is very crucial in building relationships among parties, and future studies could also benefit by examining the role of trust in the relationship. In particular, when IoT devices in smart cities are connected to the Internet, there is likelihood of attacks on these devices. From this standpoint, Saeed et al. [76] suggested that trust management is an important way to protect data from attacks; trust design models such as scalability, privacy, integrity, reliability, and accuracy associated with security mechanisms for secure communication in IoT devices could be investigated by future studies as possible mechanisms in the relationship between AI and smart decision-making in smart cities. Finally, still from the end users' perspective

future studies could benefit by examining the boundary condition (moderating) role of quality of life by adapting the model in the study.

Data Availability

The data used to support the findings of this study are available upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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