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Artificial intelligence of things: society readiness

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ABSTRACT

The convergence of artificial intelligence (AI) and the internet of things (IoT), known as the artificial intelligence of things (AIoT), represents a transformative leap in technology. This study investigated societal readiness for AIoT adoption and identified key factors influencing the readiness. The researchers used technology readiness index (TRI) model and broken down the model into the online survey's instrument. The study used about 129 samples for examining the used variables, i.e., perceptions of innovation, technological skills, social and cultural influences, regulatory factors, and digital literacy. The authors employed partial least squares structural equation modeling (PLS-SEM) method using SmartPLS 3.0 to analyze the relationships between the variables of the model. The results highlighted innovation as a significant driver of societal readiness, while factors like discomfort have a lesser impact. Security and optimism also played moderate roles in shaping readiness. These findings offer crucial insights for stakeholders of the AIoT implementation by providing a foundation for strategies that promote the successful integration of AIoT into society. The study contributes to the broader discourse on technology adoption, offering a roadmap for enhancing societal preparedness.

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1. INTRODUCTION

The implementation of artificial intelligence of things (AIoT) technology has had a profound impact on various aspects of human life. AIoT combines artificial intelligence (AI) with internet of things (IoT) to create systems that can autonomously collect, analyze, and make decisions based on data generated by interconnected devices [1], [2]. Despite its vast potential, the adoption of AIoT also presents several challenges that must be seriously considered, particularly concerning societal readiness. In this study, we aim to identify and analyze the issues arising from the deployment and use of AIoT and their impact on society's preparedness to confront them [3]. The proliferation of connected devices generating personal data raises significant concerns about data security and privacy. Threats such as data breaches, hacking, and the misuse of personal information can undermine public trust in AIoT technology. Moreover, AIoT's implementation can lead to a high dependency on technology. Any disruptions or failures in the technological infrastructure could have severe consequences across various sectors, including transportation, healthcare, and security [4]–[6]. Additionally, not everyone has equal access to AIoT technology, potentially deepening social and economic inequalities between those who have access and those who do not, resulting in uneven learning and opportunities. The enhanced automation enabled by AIoT may also lead to a reduction in human labor in certain sectors, causing structural unemployment and necessitating retraining programs to reskill workers [7].

The automatic decision-making processes by AIoT systems could raise complex ethical and legal questions [8]. For instance, who is accountable if an automated decision leads to negative consequences? How should ethical standards be applied to the use of AIoT? Furthermore, the implementation of AIoT can alter the way we interact and communicate, disrupting traditional social and cultural dynamics and creating new challenges related to social habits and norms.

Society's readiness to face these changes will play a crucial role in addressing emerging issues. It is essential for governments, industries, and educational institutions to collaborate in developing solutions that promote responsible and inclusive AIoT adoption while preparing society to effectively manage its impacts [9]. As technology continues to advance, we can expect more AIoT innovations and applications that could enhance comfort, efficiency, and quality of life across various aspects of daily living. In the context of readiness issues arising from the implementation and use of AIoT, we can relate them to the concept of the technology readiness index (TRI) proposed by Parasuraman and Colby [10]. TRI is a model used to measure the readiness of individuals or societies to adopt and use new technologies [11], [12]. In this study, we connect several aspects of TRI, i.e.: optimism, innovativeness, discomfort, and insecurity.

By connecting AIoT issues with the TRI concept, we can understand the factors influencing society's readiness to face the impacts of AIoT implementation and usage. The growing prominence of AIoT in shaping modern technology has introduced both opportunities and challenges in terms of societal readiness. While innovation is widely recognized as a crucial driver, enabling society to adapt to and embrace rapid technological advancements, the influence of other factors like discomfort and insecurity remains less explored. Innovation empowers individuals and organizations to harness new technologies, fostering a proactive approach to adoption.

However, without adequately addressing feelings of discomfort—such as fear of job displacement, loss of control, or a lack of understanding of AIoT systems—societal acceptance may be hindered. Insecurity, especially concerns around data privacy and security vulnerabilities, also plays a critical role. If individuals do not feel that their personal information is adequately protected, this can lead to hesitancy or outright resistance to engaging with AIoT technologies. Moreover, optimism towards technology has been shown to enhance societal readiness, as those with a positive outlook are more likely to explore the benefits and innovations AIoT offers.

Expanding on these interconnected factors adds depth to the analysis, revealing how each contributes to the broader societal landscape and how their nuanced roles shape both the readiness and potential resistance to AIoT adoption. Understanding these dynamics in greater detail allows for more insightful conclusions and practical recommendations for fostering societal preparedness. This study aims to investigate the extent to which these factors influence societal readiness and identify potential strategies to enhance adoption and preparedness for the AIoT revolution. The research problem for this study is: to what extent do innovation, discomfort, insecurity, and optimism influence society's readiness for the implementation of AIoT, and how can these factors be leveraged to enhance societal adoption of AIoT technology?

Therefore, this study offers valuable contributions to a more comprehensive understanding of society's preparation and response to AIoT in an era of rapidly evolving technology. Furthermore, this article is staged within four sections. The literature review section discusses the theoretical basis used in this study. The research method section will describe the methodological aspects of the study, including the research design, sample, and data analysis procedures. Next, the results and discussion section present results of the analysis stages and its comparisons with previous studies and theories, including implications, research limitations and suggestions for future research. Finally, this article closes by the conclusions section.

2. LITERATURE REVIEW

Currently, technological advancements have brought profound changes to daily life, with the concept of AIoT emerging as a new paradigm that combines AI and IoT. Various studies and implementations have highlighted the revolutionary potential of AIoT in sectors like healthcare, transportation, manufacturing, and the environment. This technology has introduced intelligent, connected devices capable of real-time data collection and analysis, providing deep insights for better decision-making. The application of AIoT has significantly impacted individual health monitoring, efficient urban traffic management, industrial supply chain optimization, and environmental conservation efforts. However, despite its promising potential, challenges such as data privacy, cybersecurity, digital literacy, and ethical issues remain prominent in research and scientific debates [13]. In this context, studying societal readiness for AIoT becomes increasingly important to understand the complex dynamics of technology adoption and its impact on various societal layers. According to intel, AIoT refers to the convergence of IoT and AI, where IoT devices are combined with AI's analytical capabilities. AIoT enables devices to intelligently collect and analyze data, producing deeper insights and supporting better decision-making. McKinsey defines AIoT as the integration of IoT with AI technologies, allowing devices to autonomously understand, predict, and respond to situations [14]. AIoT can optimize business operations, increase efficiency, and create added value through deeper data analysis [15]. Forbes describes AIoT as systems that use data generated by IoT devices and analyzed by AI algorithms to take action or produce more intelligent insights. AIoT can be applied across various industries, including manufacturing, healthcare, agriculture, and transportation [16].

The basic concept of AIoT is to combine two main technologies, IoT and AI, to create systems that are more intelligent, adaptive, and capable of making decisions autonomously [1]. IoT refers to a network of physical devices connected via the internet, capable of communicating and sharing data. These devices can range from sensors, household appliances, and vehicles to industrial equipment [17]. The main goal of IoT is to gather data from the physical environment and transmit it through networks for analysis and use in decision-making. AI is a branch of computer science focused on developing computers or machines that can perform tasks requiring human intelligence, including natural language processing, pattern recognition, machine learning, and data-driven decision-making [18]–[21]. AIoT integrates the following core concepts: data analysis—AI quickly and efficiently analyzes the vast and complex data generated by IoT devices, identifying patterns, trends, and useful insights; automatic decision-making—AIoT systems can make decisions based on data analysis and detected conditions [22]. For instance, a smart system can regulate home temperature based on weather data and resident preferences; prediction and monitoring—AIoT can predict future events based on historical data and detected factors, applicable in various industries like predicting machine failures or forecasting product demand; automatic interaction and response—AIoT systems can automatically respond to environmental changes. For example, in autonomous vehicles, AIoT helps cars recognize and react to traffic changes or emergencies; optimization and efficiency—AIoT optimizes resource use, such as energy or raw materials, based on collected data. For example, AIoT systems in agriculture can manage irrigation based on soil moisture levels; personalization and adaptation—AIoT learns from individual preferences and habits, tailoring responses to specific situations. Streaming services might suggest music based on a user's listening history; security and data management—AIoT is also used to monitor and safeguard the security of networks and the data transmitted and received by IoT devices [5], [6].

In recent years, AIoT applications have seen significant advancements, particularly in healthcare, smart homes, transportation, and education, contributing to societal transformation. Healthcare is a key sector where AIoT has made profound impacts. Devices such as smartwatches and wearable health monitors continuously track health parameters like heart rate, blood pressure, and glucose levels. This real-time data is analyzed using AI algorithms to detect abnormalities and provide early warnings to users or healthcare professionals, facilitating timely interventions and improving patient outcomes [23]. Additionally, in smart homes, AIoT systems integrate devices such as lights, kitchen appliances, and security systems, allowing for seamless management and automation. These technologies not only enhance convenience but also contribute to energy efficiency by adjusting appliance usage based on user behavior and environmental conditions. Recent research has shown that smart home technologies can lead to significant energy savings, supporting sustainability efforts [24]. In education and learning, AIoT is used to create adaptive learning experiences tailored to students' understanding and learning styles. In the realm of transportation and mobility, AIoT has driven advancements in autonomous vehicle development, with AI enabling obstacle recognition, real-time navigation, and decision-making on the road. Autonomous vehicles equipped with AIoT are becoming more sophisticated, contributing to safer driving experiences and reducing human errors [4].

The integration of AIoT in education is also transforming learning experiences. Adaptive learning platforms use AIoT to tailor educational content to individual students' needs, learning styles, and progress, offering more personalized and effective educational experiences. Recent research highlights that AI-driven adaptive learning systems have the potential to improve student engagement and learning outcomes by providing real-time feedback and customized resources [25]. Recent studies on AIoT in diverse cultural and social contexts further reveal how the adoption and societal readiness for these technologies vary. Research in East Asian countries like Japan and South Korea highlights the widespread societal acceptance of AIoT, driven by cultural values emphasizing technological advancement and innovation [26]. In contrast, studies in developing regions underscore the importance of addressing infrastructural and digital literacy challenges before AIoT can be fully integrated into society [15]. This growing body of research illustrates that while AIoT offers significant potential, its adoption is deeply influenced by social, cultural, and infrastructural factors, necessitating context-specific approaches to ensure equitable benefits across different societies.

The TRI model, developed by Parasuraman and Colby [10], measures individual readiness to adopt new technology. Parasuraman and Colby [10], plays a significant role in understanding and predicting how individuals and organizations adopt new technologies [27], [28]. This model is particularly relevant when studying the societal readiness for AIoT, as it provides a structured framework for assessing people's predisposition towards embracing technological innovations [29].

The readiness model and outer loadings in SEM-PLS in Figure 1. The TRI model is grounded in four key dimensions that reflect both positive and negative aspects of technology readiness as shown in Figure 1(a):

i) optimism: this dimension captures the positive outlook that individuals have towards technology, reflecting their belief that technology offers increased control, flexibility, and efficiency in their lives. Those with high optimism are more likely to perceive AIoT as a beneficial addition to their daily routines, viewing it as a means to enhance their personal and professional lives; ii) innovativeness measures the tendency of individuals to be pioneers or early adopters of new technologies. People scoring high in this dimension are usually the first to experiment with and integrate AIoT into their lives, often serving as opinion leaders who influence others in their social networks; iii) discomfort reflects the negative feelings that individuals may have towards technology, including a sense of being overwhelmed or out of control when interacting with new devices or systems. Those experiencing discomfort may be hesitant to adopt AIoT, fearing the complexity or potential challenges associated with its use; and iv) insecurity which pertains to concerns technology, particularly regarding privacy, security, and the reliability of technological systems. Individuals with high levels of insecurity may resist AIoT adoption due to fears about data breaches, misuse of personal information, or the inability to fully trust automated systems.

3. RESEARCH METHOD

This study employs a quantitative approach to investigate society's readiness for AIoT implementation. The data analysis method used is partial least squares structural equation modeling (PLS-SEM), which allows for the examination of complex relationships between variables and the modeling of the proposed conceptual framework [30]. The conceptual framework is developed based on concepts from the TRI model and related literature on AIoT and societal readiness [25], [30]. The study identifies key variables and connects them within a conceptual model. Data was collected through a survey distributed to 350 respondents, with 129 completed responses, covering topics such as innovation, perceived benefits, technological skills, cultural factors, regulations, and digital literacy in relation to AIoT readiness. The data underwent preprocessing for quality, including cleaning, variable transformation, and handling of missing data. Although the sample size of 129 may seem small for broader generalization, it is sufficient for this exploratory research, providing valuable initial insights. Expanding the sample size in future research would improve the findings' robustness and generalizability. Sumedang District was chosen for its diverse population in terms of socioeconomic status, education, and technological exposure, making it ideal for studying AIoT adoption. The district is also developing its technological infrastructure and has government programs promoting digital literacy and innovation. These factors make Sumedang a suitable location for examining societal readiness for AIoT, while its accessibility ensures efficient data collection.

The TRI questionnaire is designed to assess individuals' perceptions and attitudes toward technology through a structured set of variables as presented in Figure 1. It comprises five key dimensions: optimism, innovation, discomfort, insecurity, and readiness, with each dimension featuring five specific questions, resulting in a total of 25 questions. The optimism variable evaluates the positive outlook individuals have toward technology and its potential benefits, while the innovation dimension focuses on the willingness to embrace new technologies and innovations. In contrast, the discomfort variable addresses the apprehensions or challenges individuals may face when interacting with technology, and insecurity examines concerns related to data privacy and security. Finally, the readiness variable assesses the overall preparedness and willingness of individuals to adopt and utilize technology effectively. Together, these variables provide a comprehensive understanding of an individual's technology readiness.

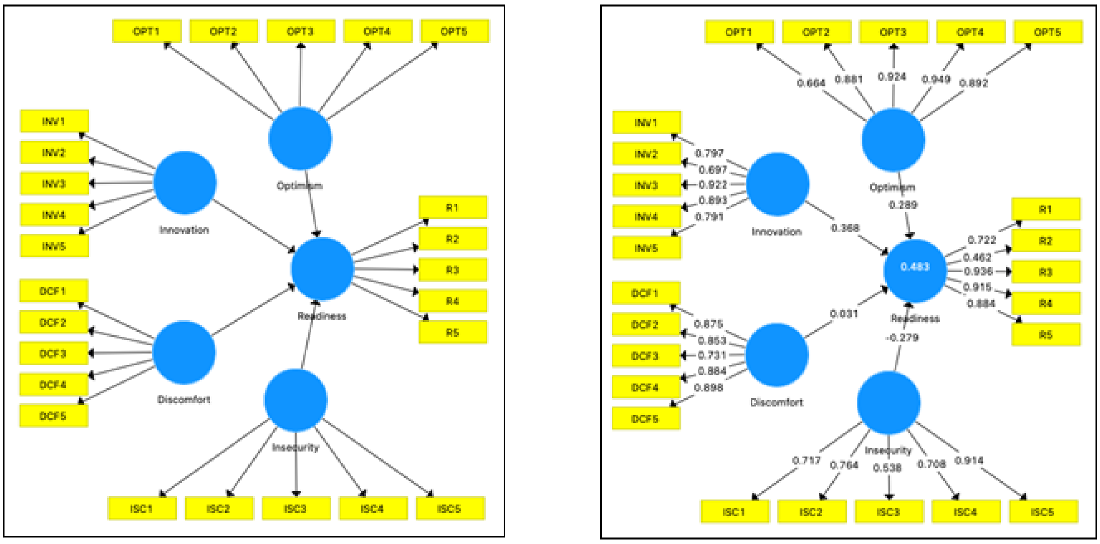
The research process begins with a literature review to identify key concepts relevant to society's readiness for AIoT implementation. Based on this review, the researcher designs the research model, including the selection of quantitative methods and the PLS-SEM analysis technique [31]. This design outlines how the research will be conducted, specifying the variables to be measured and the research model to be developed. The research population consists of the community deemed relevant for assessing their readiness for AIoT, specifically focusing on the community in Sumedang regency. The sample is drawn from this population using stratified random sampling to ensure that the selected sample is representative. Data is collected using a questionnaire developed based on the research model [32]. This questionnaire undergoes validity and reliability testing to ensure the accuracy and consistency of the collected data. Once the data is gathered, the analysis technique employed is PLS-SEM using SmartPLS 3.0, allowing the researcher to examine the relationships between variables within the model and assess how well the model explains society's readiness for AIoT [33].

The results of the data analysis are then interpreted and compiled into a research report, which includes findings, interpretation of results, and implications for future research. The research findings will be presented in a comprehensive report, incorporating graphs, tables, and diagrams to help visually explain the results. This process reflects the logical flow of systematic and structured research, consistent with the diagram that outlines the entire research process.

4. RESULTS AND DISCUSSION

The demographic respondents provide a comprehensive overview of the respondents' characteristics. The sample consists of 68% male and 32% female respondents. Age distribution reveals that 40% are between 19-29 years old, 31% fall within the 30-40 age range, 18% are aged 41-51, and 11% are 18 years old or younger, with no respondents over 51 years old. In terms of education, 60% have completed high school, 31% hold a bachelor's degree, and 9% have a master's degree. The respondents' work experience in IT is varied, with 53% having 3-6 years of experience, 31% with 7-10 years, 10% with more than 11 years, and 6% with 2 years or less. Regarding AIoT use, 50% of respondents are capable of using AIoT, while 45% are not, and 5% did not disclose their ability. Experience with AIoT also varies, with 60% having 2 years or less of experience, 30% with 3-6 years, and 10% with no experience; notably, no respondents have more than 7 years of AIoT experience. Skill levels reflect that 16% of respondents are very skilled, 11% skilled, 48% less skilled, and 25% did not disclose their skill level. Participation in AIoT training is almost evenly split, with 52% having never participated and 48% having some training experience. Support from offices is a mixed picture; 45% of respondents received training support, while 55% did not. Similarly, 63% received support in terms of facilities for AIoT use, while 37% did not, and when it comes to infrastructure support, 45% reported receiving it, while 55% did not. This demographic analysis provides crucial context for interpreting the respondents' readiness and capabilities in adopting AIoT technologies.

Internal consistency reliability is crucial as a measure of the reliability or dependability of a construct. Cronbach's alpha is one of the commonly used metrics for assessing internal consistency reliability with composite reliability (CR) value should exceed 0.708 as shown in Figure 1(b), although for exploratory research, values between 0.60 and 0.70 are often considered acceptable, in terms of in statistical and social research literature. In addition to cronbach's alpha, other metrics such as CR and average variance extracted (AVE) also assist in evaluating construct reliability within the context of PLS-SEM. Table 1 presents the CR for all reflective constructs, which exceeds 0.708, indicating a high level of internal consistency reliability. This strong consistency suggests that the indicators effectively measure their respective constructs, providing a solid foundation for further analysis. Table 2 highlights specific indicators—INV2, ISC3, OPT1, and R2—that have outer loadings below the acceptable threshold of 0.7. As a result, these indicators were removed from the model to enhance overall measurement quality. The impact of this removal was carefully analyzed, focusing on its effect on AVE and CR. If the elimination of these indicators improved these measurements, they would be permanently excluded; conversely, if no improvement was observed, the indicators would be retained. The analysis progresses in Table 3, which shows that the CR for all reflective constructs still exceeds 0.708 after the removal of the problematic indicators. This improvement reaffirms that eliminating INV2, ISC3, OPT1, and R2 has positively affected the reliability of the model. Table 4 demonstrates that all remaining reflective indicators now have outer loadings above the 0.708 threshold. In addition, some composite reliabilities have improved further. The increase in both CR and AVE after removing indicators INV2, ISC3, OPT1, and R2 confirms that this refinement has significantly enhanced the reliability and validity of the constructs within the model, ultimately strengthening the overall findings.



(a) (b)

Figure 1. Readiness model and outer loadings in SEM-PLS (a) readiness full model and (b) result of outer loading

Table 1. The first calculation values

Variable	CA	rho_A	CR	AVE
Discomfort	0.903	0.915	0.929	0.723
Innovation	0.879	0.897	0.913	0.679
Insecurity	0.855	0.868	0.853	0.545
Optimism	0.915	0.937	0.938	0.754
Readiness	0.851	0.901	0.897	0.646

Table 2. The first outer loading

	DCF	INV	ISC	OPT	R
DCF1	0.875				
DCF2	0.853				
DCF3	0.731				
DCF4	0.884				
DCF5	0.898				
INV1		0.797			
INV2		0.697			
INV3		0.922			
INV4		0.893			
INV5		0.791			
ISC1			0.717		
ISC2			0.764		
ISC3			0.538		
ISC4			0.708		
ISC5			0.914		
OPT1				0.664	
OPT2				0.881	
OPT3				0.924	
OPT4				0.949	
OPT5				0.892	
R1					0.722
R2					0.462
R3					0.936
R4					0.915
R5					0.884

Table 3. The calculation values after deletion of INV2, ISC3, OPT1, and R2 indicators

	CA	rho_A	CR	AVE
Discomfort	0.903	0.917	0.929	0.723
Innovation	0.887	0.899	0.922	0.748
Insecurity	0.823	1.032	0.865	0.618
Optimism	0.939	0.940	0.956	0.846
Readiness	0.893	0.903	0.928	0.765

Table 4. The outer loadings after indicator deletions

	DCF	INV	ISC	OPT	R
DCF1	0.874				
DCF2	0.851				
DCF3	0.730				
DCF4	0.886				
DCF5	0.899				
INV1		0.800			
INV3		0.925			
INV4		0.908			
INV5		0.820			
ISC1			0.738		
ISC2			0.759		
ISC4			0.723		
ISC5			0.911		
OPT2				0.880	
OPT3				0.938	
OPT4				0.960	
OPT5				0.900	
R1					0.704
R3					0.942
R4					0.931
R5					0.901

Table 5 clearly demonstrates that the outer loadings of the indicators for each construct are significantly higher than their cross-loadings with other constructs, as can be seen in Table 6: the cross loadings after indicator deletions. This finding indicates that each indicator is strongly associated with its respective construct, further supporting the model's reliability. Building on this evidence, Table 7 presents the results related to the Fornell-Larcker criterion, which states that the square root of the AVE for each construct should exceed the highest correlation with other constructs. This criterion is crucial for confirming discriminant validity within the model. In this case, it is observed that the square root of the AVE for each construct is indeed higher than the highest correlation with other constructs, reaffirming that each construct is more closely related to its own indicators than to those of other constructs. Additionally, the analysis of collinearity within the structural model indicates that the variance inflation factor (VIF) values for each predictor construct must be higher than 0.20 and lower than 5. If any values fall below this threshold, further considerations will be necessary to either remove the construct, combine predictors into a single construct, or create higher-order constructs to mitigate potential collinearity issues. Table 8 reinforces these findings by showing that the inner VIF values for the predictor constructs—discomfort, innovation, insecurity, optimism, and readiness—are all below 5 and above 0.2. This result indicates that collinearity among the predictor constructs is not a concern, thereby further validating the robustness of the model. Together, these tables provide compelling evidence of the model's reliability and validity, ensuring a solid foundation for the subsequent analyses.

Table 5. The firt cross loading

	DCF	INV	ISC	OPT	R
DCF1	0.874	-0.221	0.598	-0.232	-0.321
DCF2	0.851	-0.228	0.649	-0.251	-0.272
DCF3	0.730	-0.160	0.430	-0.105	-0.213
DCF4	0.886	-0.246	0.591	-0.307	-0.302
DCF5	0.899	-0.217	0.663	-0.268	-0.303
INV1	-0.296	0.800	-0.254	0.418	0.504
INV3	-0.181	0.925	-0.150	0.568	0.573
INV4	-0.240	0.908	-0.235	0.495	0.525
INV5	-0.157	0.820	-0.001	0.423	0.415
ISC1	0.475	-0.092	0.738	-0.074	-0.182
ISC2	0.509	-0.182	0.759	-0.087	-0.235
ISC4	0.658	-0.023	0.723	-0.195	-0.040
ISC5	0.644	-0.188	0.911	-0.284	-0.456
OPT2	-0.282	0.543	-0.156	0.880	0.534
OPT3	-0.207	0.517	-0.211	0.938	0.495
OPT4	-0.249	0.514	-0.268	0.960	0.540
OPT5	-0.294	0.465	-0.196	0.900	0.495
R1	-0.373	0.417	-0.387	0.418	0.704
R3	-0.261	0.577	-0.372	0.522	0.942
R4	-0.252	0.529	-0.289	0.471	0.931
R5	-0.301	0.521	-0.331	0.543	0.901

Table 6. The cross loadings after indicator deletions

	DCF	INV	ISC	OPT	R
DCF1	0.874	-0.221	0.598	-0.232	-0.321
DCF2	0.851	-0.228	0.649	-0.251	-0.272
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ISC4	0.658	-0.023	0.723	-0.195	-0.040
ISC5	0.644	-0.188	0.911	-0.284	-0.456
OPT2	-0.282	0.543	-0.156	0.880	0.534
OPT3	-0.207	0.517	-0.211	0.938	0.495
OPT4	-0.249	0.514	-0.268	0.960	0.540
OPT5	-0.294	0.465	-0.196	0.900	0.495
R1	-0.373	0.417	-0.387	0.418	0.704
R3	-0.261	0.577	-0.372	0.522	0.942
R4	-0.252	0.529	-0.289	0.471	0.931
R5	-0.301	0.521	-0.331	0.543	0.901

Table 7. Fornell Larcker's matrix

Variable	DCF	INV	ISC	OPT	R
Discomfort	0.850				
Innovation	-0.254	0.865			
Insecurity	0.695	-0.193	0.786		
Optimism	-0.281	0.555	-0.227	0.920	
Readiness	-0.336	0.589	-0.393	0.562	0.875

Table 8. Inner VIF values

Variable	DCF	INV	ISC	OPT	R
Discomfort					2.012
Innovation					1.468
Insecurity					1.937
Optimism					1.493
Readiness					

Table 9 presents the methodology used for assessing the significance of the path coefficients through bootstrapping. To ensure robust results, the minimum number of bootstrap samples should match or exceed the number of valid observations, with a recommended total of 5,000 samples. This approach guarantees that the critical values for a two-tailed test are correctly identified, with thresholds set at 1.65 (for a 10% significance level), 1.96 (for a 5% significance level), and 2.57 (for a 1% significance level). Generally, path coefficients with a p-value of 5% or less are deemed significant. For this analysis, a 5% significance level was adopted along with a one-tailed test, where a significance level of 1.64 was used. Moving on to Table 10, the focus shifts to the R^2 values of the endogenous latent variables in the path model. The primary objective of PLS-SEM is to maximize these R^2 values, indicating the model's explanatory power. While the interpretation of R^2 values can vary based on the model and research discipline, general benchmarks categorize R^2 values of 0.75, 0.50, and 0.25 as substantial, moderate, and weak, respectively. In this study, the R^2 value for the endogenous construct readiness is reported as large (substantial), emphasizing the model's effectiveness in explaining societal readiness for AIoT.

Table 9. Assessment of the significance of path coefficients

	O	M	STDEV	T	P	Results
Discomfort->Readiness	0.038	0.005	0.147	0.262	0.794	Insign
Innovation->Readiness	0.378	0.368	0.108	3.501	0.001	Sign
Insecurity->Readiness	-0.279	-0.283	0.143	1.946	0.052	Insign
Optimism->Readiness	0.299	0.296	0.114	2.635	0.009	Sign

Table 10. R-square

	R^2	R^2 adjusted
Readiness	0.488	0.459

Table 11 further enriches the analysis by presenting the f^2 values, which quantify the contributions of exogenous constructs to the endogenous latent variable Readiness. The results indicate that the contribution of the exogenous construct Discomfort is small, suggesting its limited impact on societal readiness. In contrast, the construct Innovation shows a large contribution, highlighting its significant role in shaping readiness. Additionally, the f^2 values for insecurity and optimism are categorized as medium, indicating their moderate influence on the endogenous variable.

Table 11. f-square

Variable	DCF	INV	ISC	OPT	R
Discomfort					0.001
Innovation					0.190
Insecurity					0.079
Optimism					0.117
Readiness					

Finally, Table 12 consolidates the insights gained from the previous analyses by demonstrating that the exogenous constructs possess predictive relevance for the endogenous constructs under consideration. The results from the smartPLS analysis illustrate how the f^2 values reflect the contributions of exogenous variables to the endogenous latent variables, specifically in the context of societal readiness for AIoT implementation. Together, these findings provide a comprehensive understanding of the relative importance of each exogenous construct in fostering societal readiness for AIoT technologies.

Table 12. Construct cross validated redundancy

Variable	SSO	SSE	Q^2 (=1-SSE/SSO)
Discomfort	385.000	385.000	
Innovation	308.000	308.000	
Insecurity	308.000	308.000	
Optimism	308.000	308.000	
Readiness	308.000	200.621	0.349

In discussion, the results show that innovation significantly influences societal readiness for AIoT, aligning with prior research that highlights its role in technological transformation. Innovation consistently drives adoption by fostering adaptability and forward-thinking attitudes [34]. However, a notable divergence emerges regarding the discomfort construct. Our study finds its impact on societal readiness to be low, contrasting with previous research that emphasizes comfort in technology interaction as a key factor in readiness. This discrepancy could stem from differences in the sample population, cultural context, or research methodologies [11]. For instance, discomfort may vary depending on regional or cultural attitudes toward technology, with societies exhibiting lower levels of uncertainty avoidance potentially feeling less discomfort in engaging with emerging technologies like AIoT.

The moderate impact of insecurity and optimism on readiness aligns with research emphasizing data security and positive perceptions in fostering societal adoption. Insecurity highlights broader concerns about privacy and trust in AIoT systems, potentially hindering adoption if not adequately addressed. Optimism, on the other hand, contributes to a more open-minded and future-oriented perspective, encouraging societal readiness [35]. These findings highlight the dual impact of technological optimism and security concerns on AIoT adoption. Research, such as Hofstede's cultural dimensions theory, offers insights into how cultural traits like uncertainty avoidance, collectivism, and power distance shape societal responses. High uncertainty avoidance may hinder AIoT adoption due to fear of unpredictability, while collectivist cultures may embrace it to enhance community well-being. Conversely, in individualistic societies, AIoT adoption might be driven more by personal benefit and innovation [35]. Cultural perspectives influence perceived benefits and risks of AIoT adoption. In regions where technology symbolizes progress, societal readiness tends to be higher. Conversely, in tradition-oriented societies, greater efforts are needed to promote awareness of AIoT's benefits and safety [35]. In summary, while innovation, security, and optimism drive societal readiness, integrating social and cultural dimensions provides a deeper understanding of AIoT adoption. Recognizing diverse technological approaches enables future research to address cultural variability, fostering targeted strategies for AIoT readiness. This perspective underscores the need for both technological and cultural readiness, contributing to a more holistic understanding of societal transformations amid rapid technological change.

5. CONCLUSION

This study provides valuable insights into society's readiness for the implementation of AIoT. Through F2 analysis, the relative contribution of exogenous constructs to the endogenous latent variable readiness was identified. The results indicate that innovation factors significantly influence society's readiness for AIoT, with innovation being the primary driver, preparing society to face rapid technological transformation. Conversely, the discomfort factor has a low impact, suggesting that comfort in interacting with AIoT technology is less significant in shaping readiness. The factors of insecurity and optimism have a moderate influence on societal readiness. These findings underscore the importance of security and optimism in stimulating the adoption of AIoT technology. Based on these findings and conclusions, several recommendations can be made for further development: i) focusing on innovation is crucial in preparing society for the AIoT era. Developing active innovation programs and technology education can help the public better understand the potential of AIoT and the benefits it can bring, ii) raising awareness about the importance of data security and fostering optimism toward AIoT technology will help society feel more confident and prepared for technological change. Information campaigns and education on data protection measures and AIoT benefits can help address concerns and enhance readiness, and iii) future studies could explore other factors that may influence societal readiness for AIoT, such as cultural aspects, regulations, and other social factors.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors confirm that there are no competing interests associated with this publication.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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