"The transformative power of recommender systems in enhancing citizens' satisfaction: Evidence from the Moroccan public sector"

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THE TRANSFORMATIVE POWER OF RECOMMENDER SYSTEMS IN ENHANCING CITIZENS' SATISFACTION: EVIDENCE FROM THE MOROCCAN PUBLIC SECTOR

Abstract

The study aims to specifically evaluate the potential impact of implementing AI-powered recommender systems on citizen satisfaction within Moroccan public services. As part of its ambitious digital transformation, Morocco is integrating digital technologies into its public sector to enhance service delivery. Recommender systems, by providing personalized, timely, and relevant recommendations, are hypothesized to significantly increase citizens' satisfaction and transform public service delivery. The study highlights a comprehensive model that captures the complex and interrelated factors influencing recommender system success. This model was tested using Smart PLS (Partial Least Squares) on data collected from a diverse sample of 157 Moroccan citizens. These participants were randomly selected from various demographics and regions to represent the general population's perspectives on the future implementation of AI-powered recommender systems in public services. The survey tested three hypotheses: the positive relationship between the potential use of recommender systems and anticipated citizen satisfaction (supported; b = 0.694, p = 0.000, t = 21.214), the impact of trust in AI-powered recommender systems on anticipated citizens' satisfaction (supported; b = 0.543, p = 0.000, t = 14.230) ; and the moderating effect of trust on AI-powered recommender systems showing a positive effect on anticipated satisfaction (supported; b = 0.154, p = 0.000, t = 4.907). These findings suggest that the future integration of AI-powered recommender systems into public services can enhance citizens' satisfaction, particularly where there is high trust in the technology.

Keywords public sector, recommender systems, trust, citizens' satisfaction, AI-powered recommender systems

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INTRODUCTION

In today's rapidly changing global landscape, governments worldwide are faced with the imperative to modernize their public administration systems to meet the evolving needs and challenges of society. This transformation not only seeks to enhance service delivery to citizens but also aims to leverage information technology to create public value (Stoker, 2006), and promote transparency and responsiveness in governance (Bannister & Connolly, 2014). In the evolving landscape of societal digitalization, there is a notable surge in the prioritization of electronic government (e-gov) initiatives marking a significant shift in citizen-government interaction following the digital e-commerce revolution (Islam & Ehsan, 2013). With the growing utilization of e-government services by citizens, a new framework of expectations arises concerning governmental interactions (West, 2004).

However, critics contend that online public services often neglect user needs, prioritizing technological capabilities instead (Lindgren &

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Jansson, 2013), underscoring the necessity for tailored technologies that enhance both the effectiveness of e-services and user satisfaction (Špaček & Špačková, 2023). Recommender systems (RS) emerge as promising tools in the realm of e-governance, leveraging extensive data, content, and services accessible through government applications. These systems can be tailored to address the diverse needs of various stakeholders (Cortés-Cediel et al., 2017). Nonetheless, research on RS in e-governance remains limited, with most studies focusing on facilitating citizen-business interactions or providing personalized government notifications and services (Cortés-Cediel et al., 2017).

1. LITERATURE REVIEW AND HYPOTHESES

Recommender systems in Moroccan public services are gaining attention for their potential to enhance communication and governance, these systems are vital for addressing citizens' needs and preferences. Despite these advancements, challenges remain in communication, governance, and cost control within Moroccan public administration. The country's new constitution emphasizes the importance of accessible public services and transparency necessitating the development of effective digital platforms that enable dependable and efficient public communication (Jeddou & Oulhadj, n.d.).

In contrast to the previously discussed concepts, trust plays a significant role, as users need to trust that the system can handle their personal information in a secure manner and deliver recommendations that accurately reflect their preferences and interests (Liu & Wang, 2024).

As technology continues to advance, the integration of artificial intelligence (AI) into various sectors, particularly in the realm of recommender systems, has garnered significant attention. The integration of artificial intelligence (AI) into a variety of systems and applications including recommender systems (RS) has grown significantly. Recommender systems (RS) are critical constituents of artificial intelligence (AI) due to their capability of customizing content and services for each user (Zhang et al., 2021).

Kumar et al. (2023) claim that, in the public sector, recommender systems (RS) improve citizens' satisfaction by offering tailored public service recommendations. Furthermore, recommender systems (RS) employ various algorithms, such as collaborative filtering, content-based filtering and hybrid techniques, to generate suggestions based on users' historical activity and preferences (Kumar et al., 2023).

Additionally, artificial intelligence (AI) methods like natural language processing and machine learning have been integrated into RS to improve their efficacy and accuracy (Zhang et al., 2021).

It needs to be noted that recommender systems (RS) have arisen to assist users in discovering content that is truly relevant to their needs. According to Ricci et al. (2010), RS assist users in decision-making through data mining, information filtering, and prediction algorithms, providing a range of choices aligned with their interests. These systems play a vital role in navigating customers through extensive databases of information and tailoring suggestions to their individual needs and objectives (Yakhchi, 2021).

The private sector has driven the shift in digital platforms organization to optimize user engagement and financial gain through personalized content (Hildén, 2022).

However, in the public sector, privacy and ethical data usage concerns must be addressed to build public trust through transparency and fairness (Alexander, 2022).

Hence, to guarantee their compatibility with democratic principles and ability to address the common welfare of society, the development and implementation of these systems necessitate an alliance between policymakers, technologists, and general public (Hildén, 2022). In summary, the integration of AI into RS has revolutionized content recommendation by offering personalized suggestions to users. However, ethical and privacy concerns, particularly in the public sector, highlight the need for collaboration among stakeholders to ensure the responsible development and deployment of these systems for the benefit of society.

Following the examination of AI-powered recommender systems, the focus of the study shifts towards understanding the critical elements of trust in technology acceptance. Trust significantly impacts user satisfaction and technology acceptance. In an e-commerce environment they have discovered that higher levels of trust lead to greater usage, perceived benefits, and reduced risk perceptions (Kim et al., 2009).

Besides, Lin (2014) states that when people lack information and expertise with an innovation, significant level of uncertainty trust becomes vital.

Thus, when confronted with the decision of whether to support or oppose technology, individuals depend on social trust, which is given by authorities or experts (Siegrist & Cvetkovich, 2000). Although defining citizens' trust in government varies, is it widely acknowledged as crucial for public cooperation and action.

Kunkel and Ziegler (2023) show that trust in AI-powered recommender systems correlates positively with user's satisfaction. This suggests that establishing trust in the recommendations provided by AI-powered systems is essential for enhancing user experiences and driving acceptance of these technologies in various domains.

In summary, trust serves as a foundational element in shaping user attitudes towards technology, influencing their satisfaction levels and acceptance of innovations such as AI-powered recommender systems. Establishing and maintaining trust is essential for fostering positive user experiences and encouraging widespread adoption of technology across different contexts.

Building upon the exploration of trust, the discussion now turns towards citizen satisfaction as a fundamental metric of service effectiveness .According to Cardozo (1965) public satisfaction is defined as the perception of a service or product compared to expectations. Based on Cardozo's (1965) findings, it remains clear that high satisfaction occurs when service levels meet or exceed expectations. Various theoretical models from marketing have been adapted to government contexts to understand public attitudes toward services.

Consequently, many developing countries have attempted to implement e-government models similar to developed nations, expecting similar benefits. However, significant gaps in service acceptance have led to failures in establishing electronic government services (Heeks, 2003). This was owing to significant gap that existed between the users and the platform, this was mainly attributable to the low level of service acceptance.

Susanto and Goodwin (2013) identified attitude, mentality, social demographic factors, anticipated benefits and the service provider (the government in the case of e-government) are the psychological drivers that influence the actions and behavior of individuals interested in utilizing e-government services. Understanding these drivers is essential for designing effective strategies to promote the adoption and utilization of e-government services.

In summary, the concept of public satisfaction, as delineated by Cardozo (1965), underscores the importance of meeting or exceeding user expectations in service delivery. However, despite efforts to implement e-government initiatives worldwide, significant challenges persist, largely due to discrepancies between user expectations and actual service delivery. Recognizing the psychological drivers that influence user behavior is essential for addressing these challenges and fostering greater acceptance of e-government services. Given this context, there arises a critical need for further research to explore the future implementation of recommender systems in the public sector. Thus, this study endeavors to investigate the potential impact, challenges, and benefits of implementing AI-powered recommender systems to enhance citizens' satisfaction and trust in the public sector.

Additional studies are needed to address the many unanswered questions and inconsistencies revealed by combining the current literature on AI-powered recommender systems, citizen satisfaction and trust in the technology. The adoption of recommender systems in the public sector is still relatively limited compared to the private sector.

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Several challenges remain unaddressed in AI-powered recommender systems despite their progress, given the growing landscape of AI technologies, there is a pressing need to explore further into the process behind citizens' satisfaction and trust in AI-powered recommender systems. An in-depth investigation of the relationship between trust, satisfaction, and system performance in artificial intelligence can provide insights into the fundamental processes that are responsible for user experiences.

Building upon the imperative for deeper exploration into user experiences, the Expectation Confirmation Theory (ECT) offers a pertinent lens through which to examine the dynamics of satisfaction and trust in AI-powered recommender systems. According to the Expectation Confirmation Theory (ECT), individuals establish certain expectations about a service or products and feel satisfied when their experience with those services aligns with their perceived notions (Lin et al., 2009). In the context of recommender systems (RSs), citizens approach government digital services with specific expectations about the relevance, accuracy, and personalization of the information and services they will receive (Saguin, 2013). Thus, the mechanism of expectation confirmation (ECT), offers a theoretical foundation for comprehending how recommender systems can lead to higher citizen satisfaction (Rubens et al., 2015).

Furthermore, the service quality model also offers a detailed framework for evaluating how recommender systems affect citizens' satisfaction. This model identifies essential elements such as responsiveness, consistency, certainty, and tangibility are the main dimensions, by incorporating each dimension into recommender systems a distinct viewpoint on service quality is presented, emphasizing the significance of process and interaction quality (Seth et al., 2005).

Consequently, integrating the perspectives derived from ECT with the emphasis on service quality in the SERVQUAL model provides a more nuanced view of how recommender systems can improve the level of satisfaction experienced by citizens.

According to Kunkel and Ziegler (2023), trust in AI-powered recommender systems is positively correlated with user satisfaction. This finding underscores the significant role of trust in consumer perceptions of these systems. Trust in AI-powered recommender systems is influenced by such factors as impartiality and transparency. For example, Ge et al. (2024) found that the perceptions of impartiality impacted users' trust in AI-powered recommender systems, while Toreini at al. (2020) identified that transparency and explicability as key in establishing trust in such systems. Collectively these studies suggest that citizen satisfaction is positively influenced by trust in AI-powered recommender systems.

Consequently, the study predicts that government agencies can increase the adoption and utilization of AI-powered recommender systems and enhance public satisfaction by fostering trust through transparency, data privacy and security.

The integration of recommender systems into public services, which aims to improve user satisfaction, is heavily reliant on citizens' trust in these systems (Wang et al., 2022). Also, the risk-based story of trust becomes important when users encounter uncertainties concerning the precision of recommendations or concerns regarding data security and privacy.

Additionally, trust enhances of the perceived utility of recommendations, thereby increasing their perceived relevance and value to the user. Pavlou (2003) integrates trust into the technology acceptance (TAM) providing insights into how trust affects perceptions of technological usefulness and acceptance.

The research indicates that individuals' acceptance, satisfaction and usage behavior are affected by the level of trust they place in technological innovations and the manner in which they interact with them. Based on the findings of Mayer et al. (1995) and Rahi et al. (2017), this study hypothesizes that the relationship between the use of recommender systems and citizen satisfaction will be moderated by trust in AI-powered recommender systems.

In summary, addressing the gaps and inconsistencies in current literature through further research can provide valuable insights into the processes behind citizen satisfaction and trust in

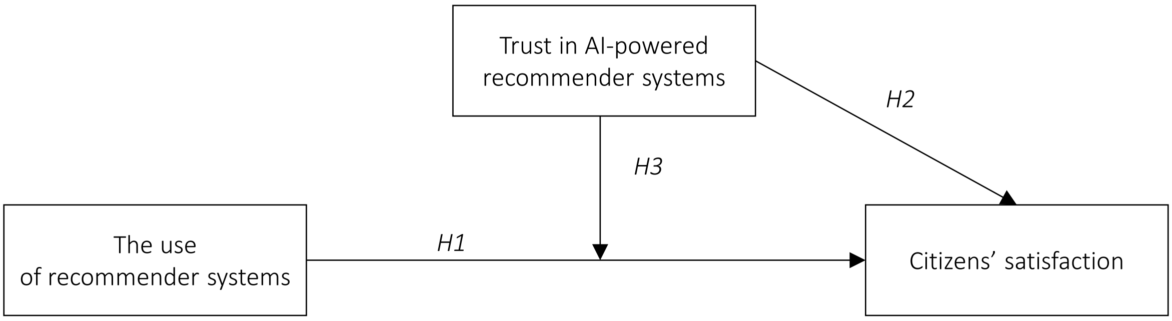

Figure 1. Research model

AI-powered recommender systems. By fostering trust and aligning system performance with user expectations, government agencies can enhance public satisfaction and increase the adoption and utilization of AI-powered recommender systems in public services.

After reviewing the studies, the following hypotheses are formulated:

H1: *The use of recommender systems positively impacts citizens' satisfaction.*

H2: *Trust in AI-powered recommender systems positively impacts citizens' satisfaction.*

H3: *Trust in AI-powered recommender systems moderates the relationship between the use of recommender systems and citizens' satisfaction.*

Figure 1 showcases the synthesized conceptual model incorporating all pertinent elements central to operationalizing this study.

2. METHODOLOGY

As a research tool, this study used a questionnaire that borrowed items from recognized and validated measurement scales in the recommender systems literature. The following items, which assess citizens' satisfaction with AI-powered recommender systems, were taken from the scale (Pu et al., 2011) established to gauge citizens' satisfaction with these systems. During the empirical phase, the operationalization of citizens' trust in AI-powered recommender systems was conducted using the scale developed by O'Donovan and Smyth (2005). Both sources have strong validity and internal consistency, which means that this decision will provide solid and exploitable findings worldwide.

The satisfaction levels of citizen were assessed using a four-point Likert scale, which corresponds to the user satisfaction scale for recommender systems (Pu et al., 2011) from "strongly disagree" (one) to "strongly agree"(four). A four-point Likert was also used in the procedure, which was in accordance with the guidelines for the trust in recommender systems scale, the scale ranged from one which indicated also strongly disagree" (one) to "strongly agree" (four). Appendix A provides comprehensive information regarding the questionnaire.

The quality of the questionnaire was ensured through the implementation of multiple processes, through collaboration with varied set of experts spanning and practitioners within the public sector, these experts had reviewed the survey questions with great care to verify that they were appropriate. The construct measurement was formulated in accordance with prior research.

To pilot test the model, a survey instrument was administered, to a diverse sample of 200 Moroccan citizens. The survey was designed to target individuals who have interacted with digital services in the public sector, ensuring they could provide informed insights about the future implementation of recommender systems. This was achieved by including specific questions about their past experiences with various digital services. The study employs a non-probabilistic sampling approach, to assess the impact of AI-powered recommender systems in Moroccan public services. This meth-

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od was chosen to effectively reach specific users of digital public services. The study focuses on a diverse sample of Moroccan citizens who have utilized digital public services, and this population is directly relevant to the research objective.

Data collection began in early November until the end of February, printed questionnaire was distributed to citizens in the city of Fez, online version was proposed via Google forms, online version was shared with other citizens to efficiently reach a large number of respondents. In total, only 157 responses were collected 31 of them were obtained through the printed version, this response rate reflects several factors, including the availability and interest of potential respondents, as well as the time required to complete the survey.

The number of 157 respondents may seem limited as first glance, but it is important to understand the context and practical constraints of the study. First, the respondents of the study are those who have actually used digital public services. This enhances the relevance of the collected responses, as they come from users with direct experience with some digital services.

Given the study's focus on the future implementation of recommender systems, there was a challenge in engaging citizens who might not yet feel invested in these systems. Even though the non-probabilistic approach is not the most robust form of sampling, it was deemed necessary under these circumstances and remains one of the study's limitations (Creswell et al., 2003).

Data collection was conducted over an extended period with several follow-ups to maximize the response rate. Despite these efforts, the online data collection process can face challenges such as participant engagement and communication interruptions.

Lastly, while the number 157 may appear modest, it is sufficient for the analysis based on the Partial Least Squares (PLS) approach. This method is well-suited for modest sample sizes and allowed us to effectively test the research hypotheses with statistically significant results.

This study employed the Structural Equation Modeling (SEM) technique to analyze the model and hypotheses. Specifically, the study applied the Partial Least Squares (PLS) method, which is suitable to test complex models and latent variables.

Table 1 presents the gender distribution of the survey respondents, out of 157 respondents, 54.14% were male and 45.86% were female.

Table 1. Sample distribution across gender and age

Gender	Frequency (f)	%
Male	85	54.14
Female	72	45.86

Table 2 provides a detailed breakdown of the respondents by age and qualification level. The majority of respondents (74.52%) are aged 18-30 reflecting a younger demographic likely more engaged with digital services. A significant portion (22.93%) falls within the 31-45 age range. A small percentage (1.9%) of respondents are aged 46-60, and only 0.64% are over 60 years old. 31.85% of respondents reported having completed high school or less, highlighting a significant portion with foundational education.(44.59%) indicated they hold a Bachelor's degree. This suggests a substantial number of respondents have pursued higher education, potentially influencing their engagement with digital services. 19.11% reported having a master's degree. 4.46% fell into the "other" category, encompassing various educational backgrounds such as vocational training or other qualifications not specified.

Table 2. Age and qualification level distribution

Age			Qualification level		
Range	Frequency (f)	%	Degree	Frequency (f)	%
18-30	117	74.52	High school or less	50	31.85
31-45	36	22.93	Bachelor's degree	70	44.59
46-60	3	1.91	Master's degree	30	19.11
60+	1	0.64	Other	7	4.46

3. RESULTS

Table 3 shows that there is a substantial positive association between the use of recommender systems and the level of satisfaction experienced by citizens, as shown by the path coefficient value of 0.694. Given the p-value of 0.000 for a statistically significant association, high t-value suggests that recommender systems significantly improve citizens' satisfaction.

The path coefficient of 0.543 shows that trust in AI-powered recommender systems increases citizens' satisfaction, the p-value for this association is 0.000, and t-value for it is 14.230, which indicates that it is statistically significant.

Trust in AI-powered recommender systems is a crucial factor that positively influences the level of satisfaction experienced by citizens', with a path coefficient of 0,154, showing a powered positive impact on citizens' satisfaction, and p-value of 0.000 and t-value of 4.907, indicating that this association is statistically significant.

In the analysis of the construct related to the use of recommender systems (as presented in Figure 2 and Table 4), indicators Q13, Q14, Q15, and Q16 exhibit loadings ranging from 0.755 to 0.803, suggesting a strong relationship with the construct. Cronbach's Alpha for this construct is 0.794, indicating excellent internal consistency among these indicators. Additionally, Composite Reliability is reported at 0.886, and Average Variance Extracted (AVE) is 0.618, both demonstrating that the construct is well-defined and the indicators are reliably measuring it.

Regarding the construct of citizen satisfaction, measured by indicators Q20, Q21, and Q22, the loadings range between 0.917 and 0.942, which indicate strong relationships with the construct. Cronbach's Alpha for this set is 0.918, suggesting good internal consistency, while Composite Reliability is 0.760, again indicating excellent reliability. The AVE of 0.859 reflects very good construct validity.

Finally, the construct of trust in AI-powered recommender systems, measured by indicators Q17, Q18, and Q19, shows loadings from 0.865 to 0.819. Cronbach's Alpha is 0.867, and Composite Reliability stands at 0.876, both of which signify good internal consistency. The AVE is 0.790, indicating strong construct validity.

Overall, the indicators for each construct show robust relationships with their respective constructs, demonstrating that the questions are well-selected. The consistently high values of Cronbach's Alpha, Composite Reliability, and AVE across all constructs affirm that the measurement model is robust, with the constructs being well-defined and effectively measured.

Table 3. Hypotheses testing

Hypotheses	Path coefficients	p-value	t-value	Support
H1: Use of recommender systems → citizens' satisfaction	0.694	0,000	21.214	Yes
H2: Trust in AI-powered recommender systems → citizens' satisfaction	0.543	0.000	14.230	Yes
H3: Trust in AI-powered recommender systems x recommender systems → citizens' satisfaction	0.154	0.000	4.907	Yes

Table 4. Standardized loadings, reliability, and validity

Constructs	Type of measure	Indicators	Loadings	Cronbach's Alpha	Composite reliability	AVE
Use of recommender systems	Reflective	Q13	0.803			
		Q14	0.785			
		Q15	0.801	0.794	0.886	0.618
		Q16	0.755			
Citizens' satisfaction	Reflective	Q20	0.942	0.918	0.760	0.859
		Q21	0.921			
		Q22	0.917			
Trust in AI-chatbots	Reflective	Q17	0.919	0.867	0.876	0.790
		Q18	0.865			
		Q19	0.882			

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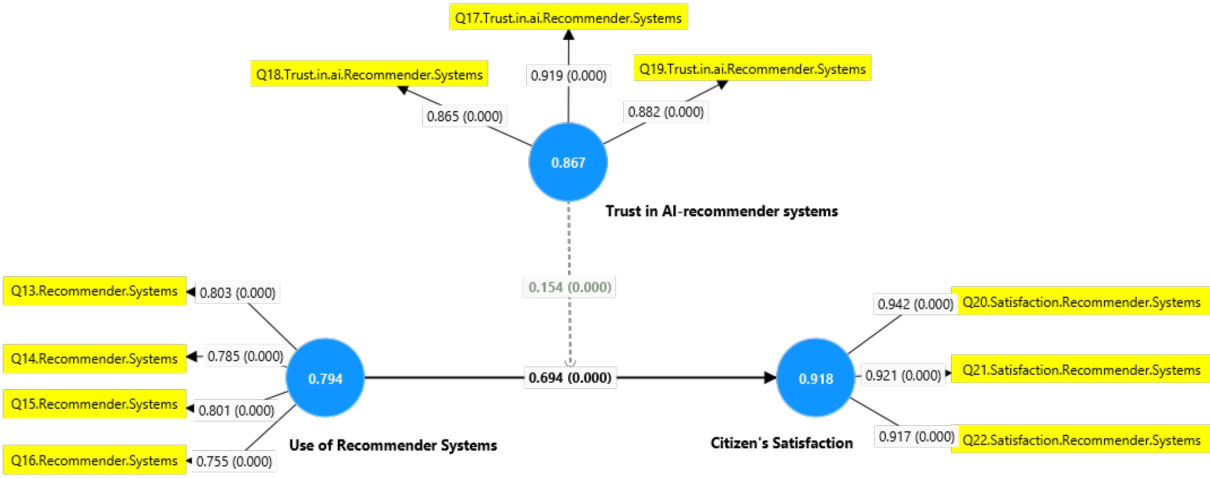

Figure 2. Results of the conceptual model

Table 5 reports the Fornell-Larcker criterion for discriminant validity demonstrates that each model construct citizen satisfaction, trust in AI-powered recommender systems, and use of recommender systems is unique from the others. The diagonal elements representing the square roots of the Average Variance Extracted (AVE) for each construct exceed the inter-construct correlations, as required by the Fornell-Larcker criterion. Specifically, citizen's satisfaction has an AVE of 0.927, trust in AI-powered recommender systems has an AVE of 0.889, and the use of recommender systems has an AVE of 0.786. The model thus has sufficient discriminant validity, indicating that the constructs are empirically distinct and contribute independently to the model.

The model fit was determined using the standardized root mean squared residual (SRMR). According to Table 6, the SRMR value is 0.065, which is considered acceptable range of 0 to 0.08, as defined by Hu and Bentler (1999), demonstrating that the model fit is acceptable.

The results of the HTMT ratio presented in Table 7 show that all the values are below the threshold of 0.9 (Hult et al., 2018). Thus, discriminant validity is established.

Table 5. Fornell-Larcker criterion for discriminant validity

	Citizens' satisfaction	Trust in AI-powered RS	Use of recommender systems
Citizens' satisfaction	0.927		
Trust in AI-powered recommender systems	0.627	0.889	
Use of recommender systems	0.747	0.120	0.786

Table 6. Standardized root mean squared residual

SRMR	Saturated model	Estimated model
	0.065	0.065

Table 7. HTMT criterion test result

Criterion	CS	Trust in AI-powered RS	Use of RS	Use of RS	Trust in AI-powered RS
Citizens' satisfaction	–	–	–	–	–
Trust in AI-powered recommender systems	0.699	–	–	–	–
Use of recommender systems	0.873	0.150	–	–	–
Trust in AI-powered recommender systems	0.094	0.041	–	0.102	–

4. DISCUSSION

The study discusses valuable insights into the complex relationships between implementation of recommender systems, trust in AI-powered recommender systems, and citizens' satisfaction.

Firstly, the study supports the hypothesis *H1* that adopting recommender systems increases citizens' satisfaction, this finding applies with earlier studies that demonstrated the positive effects of AI-powered decision support systems in enhancing user experiences and satisfaction levels (Fields et al., 2018).

Additionally, the findings of this study show that the result of the hypothesis *H2* is consistent with previous studies that have highlighted the crucial role of trust in the adoption and use of recommender systems.

Moreover, several studies examined the influence of trust on user satisfaction. For instance, according to research by Komiak and Benbasat (2004), user satisfaction is greatly affected by trust. Similarly, Gefen (2003) emphasized the importance of trust in predicting customer satisfaction through an integrated model of trust and the Technology Acceptance Model (TAM) in online purchasing.

Interestingly, the study reveals a positive interaction effect between trust in AI-powered recommender systems and the use of recommender systems on citizens' satisfaction. This suggests that when both trust in AI-powered recommender systems and use of these systems are high, a synergistic effect occurs, increasing citizens' satisfaction. These findings have significant implications for policymakers' community and public service providers.

First, the study highlights the importance of prioritizing the successful implementation of recommender systems in public services to improve citizens' satisfaction. Second, the study applies established trust theories to the largely unexplored field of public service recommender systems. Third, as trust in AI-powered recommender systems affects directly citizens' satisfaction (*H2*), trust in these systems moderates the relationship between these systems and citizens' satisfaction (*H3*).

In this regard, the application of the risk-based theory of trust elucidates the intricate functions of trust in such environments, implying that the dynamics of trust that are observed in commercial contexts are equally relevant in the public sector.

Is it important to note that incorporating trust as a moderator in the relationship between technology use and satisfaction (*H3*) offers a novel extension to existing Technology Acceptance Model (TAM). It suggests that trust is a critical factor that influences user satisfaction and continued use, which enriches the predictive power of (TAM) in the context of e-government services.

Consequently, developing trust in AI-powered recommender systems should be a top priority since trust can play an important role in moderating the relationship between using these systems and citizens' satisfaction.

Furthermore, the unified theory of acceptance and use of technology (UTAUT) is an example of a model that could be improved by the utilization of the new information that has been obtained. To the extent that four core constructs; performance expectancy, effort expectancy, social influence, and facilitating conditions are the main determinants of technology adoption and use, according to the UTAUT model created by Venkatesh et al. (2003), trust in AI-powered recommender systems might be a useful addition to the model as a moderating variable.

These findings hold significant implications for policymakers, communities, and public service providers. First and foremost, the study underscores the importance of prioritizing the successful implementation of recommender systems in public services to enhance citizens' satisfaction. Additionally, it advocates for the prioritization of building trust in AI- powered recommender systems, as trust plays a pivotal role in moderating the relationship between the utilization of these systems and citizens' satisfaction. These recommendations echo broader calls in the literature for user-centered design and transparent communication in technology adoption initiatives (Norman, 2013.)

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CONCLUSION

This study aimed to design and empirically evaluate a theoretical model based on institutional theory to understand the impact of recommender systems on citizens' satisfaction in the public sector, particularly within the Moroccan e-government context.

The empirical findings of the study demonstrate that recommender systems significantly enhance citizens' satisfaction by improving service quality and customization in e-government services. The implementation of these systems could lead to substantial improvements in service delivery. Additionally, the study highlights the importance of building trust in AI-powered recommender systems as a critical factor influencing their acceptance. The study offers a novel extension to existing technology acceptance models by incorporating trust as a moderating variable, thereby enhancing the predictive power of these models in the context of e-government services. It advocates for the prioritization of trust building measures to maximize the benefits of AI-powered recommender systems in the public sector.

Future research should explore the role of different trust metrics in shaping user perceptions and satisfaction with AI-powered recommender systems. Investigating how contextual variables impact the relationship between trust in AI-powered recommender systems, their usage and citizens' satisfaction could provide a more comprehensive understanding of these dynamics.

Additionally, is it crucial to examine potential issues of bias, discrimination and fairness arising from these systems should be thoroughly examined to ensure ethical deployment.

AUTHOR CONTRIBUTIONS

Conceptualization: Ouissale El Gharbaoui, Hayat El boukhari, Abdelkader Salmi.
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Formal analysis: Ouissale El Gharbaoui, Abdelkader Salmi.
Investigation: Ouissale El Gharbaoui, Hayat El Boukhari.
Methodology: Ouissale El Gharbaoui, Hayat El Boukhari.
Project administration: Ouissale El Gharbaoui, Hayat El Boukhari.
Supervision: Hayat El Boukhari.
Software: Ouissale El Gharbaoui, Abdelkader Salmi.
Validation: Ouissale El Gharbaoui, Hayat El Boukhari, Abdelkader Salmi.
Visualization: Ouissale El Gharbaoui, Abdelkader Salmi.
Writing – original draft: Ouissale El Gharbaoui.
Writing – review & editing: Ouissale El Gharbaoui.

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APPENDIX A

Table A1. Use of recommender systems, trust in AI-powered recommender systems and citizens' satisfactions measures

Construct	Measure
Use of recommender systems	1: I believe that the future implementation of recommender systems in government services would greatly enhance my interactions? 2: I believe that the implementation of recommender systems in the public sector would improve the efficiency of service delivery? (Torfing, Sørensen, & Røiseland). 3: I expect that using recommender systems in the future would be beneficial in guiding my decision-making process. 4: In the future, I foresee being able to effectively communicate my preferences to the recommender system.
Trust in AI-powered recommender systems	1: I anticipate being able to easily place my trust in recommender systems once they are implemented in the future. 2: I have a tendency to place my trust in AI-powered recommender systems despite possessing limited knowledge of these systems ((Wang & Benbasat, 2008); (Lee & Turban, 2001). 3: I believe that in the future, I will feel secure relying on the recommendations provided by AI-powered recommender systems.
Citizens' satisfaction	1: I believe that using recommender systems in the future would increase my satisfaction with public services. 2: I believe that my level of trust in AI-powered recommender systems has a significance influence on my overall satisfaction (Welch, Hinnant, & Moon, 2005). 3: I think that trust in AI-powered recommender satisfaction enhances the relationship between using these systems and my satisfaction with the recommendations.

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