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Assessing Smart Service Adoption in South African Townships: An Extended UTAUT Framework

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Abstract The concept of smart cities has emerged globally in response to rapid urban migration. However, in South Africa, many citizens still live on the peripheries of urban centers due to spatial and socio-economic inequalities stemming from apartheid, which displaced and marginalized township and rural populations. This study explores the factors influencing the adoption and acceptance of smart services in South African townships and assesses the moderating effects of the Unified Theory of Acceptance and Use of Technology (UTAUT) variables. To enhance the UTAUT framework, the study incorporates trust, self-efficacy, and perceived risk as additional constructs. A random survey was distributed to township residents, with a targeted sample size of 384. A total of 472 valid responses were analyzed. The findings reveal that social influence, trust, perceived risk, income, and education significantly determine smart service adoption. Furthermore, age, gender, income, and education were found to moderate user behavior, impacting both acceptance and practical use of these services. The results offer valuable insights for policymakers and service providers in townships, highlighting the importance of understanding the roles of social influence, trust, security, income, and education. These insights can guide the development of inclusive smart services, tailored awareness campaigns, secure technologies, and targeted digital skills programs, ensuring that smart service initiatives are equitable and effective in township contexts.

Keywords: UTAUT, smart services, acceptance, and smart services use, smart township, smart service adoption

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1. INTRODUCTION

The smart city concept has become a central theme in urban planning worldwide, offering the promise of environmental sustainability, improved operational efficiency, and enhanced citizen engagement [1–3]. Smart cities aim to strengthen municipal infrastructure management by integrating critical services such as electricity, sanitation, and transportation. In some contexts, private smart city initiatives have demonstrated success in reducing crime and leveraging real-time data to optimize city operations [4]. Internationally, cities such as Toronto, New York City, Barcelona, and Sydney stand as notable examples of advanced smart city implementation. Within Africa, countries including Ghana, Côte d'Ivoire, Senegal, and Nigeria have established innovation hubs and incubation centres that promote competition and support the growth of smart city concepts [2],[3].In South Africa, the adoption of smart city initiatives has gained momentum in metropolitan areas such as Cape Town, Ekurhuleni, and Johannesburg [5].

However, progress remains uneven. The legacies of apartheid spatial planning continue to shape urban development, leaving many township communities physically distant from economic centres and underserved in terms of infrastructure and service delivery. These historical inequalities contribute to current socio-economic challenges, including limited access to basic services, constrained mobility, and reduced economic participation [5],[6]. As a result, residents often prioritise essential needs—such as housing, road infrastructure, and reliable water access—over technologically advanced solutions [3].

Yet, it is precisely within this context of persistent inequality that smart services present meaningful opportunities. When appropriately designed and locally adapted, smart solutions can help address historical service gaps by improving resource distribution, enhancing safety, expanding access to information, and facilitating more participatory forms of governance [2],[5],[7]. Geographic conditions, resource availability, and socio-economic dynamics therefore become critical considerations in determining how smart city initiatives can be leveraged to bridge long-standing disparities rather than deepen them [8],[9]. In light of these dynamics, this study contributes a novel perspective by applying an extended UTAUT framework to examine the acceptance and use of smart services in South African townships. While UTAUT has been widely used in technology adoption research, its application within the unique socio-historical and infrastructural

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context of townships remains limited. By incorporating additional factors such as trust, security, income, and education, this study offers a more context-sensitive understanding of smart service adoption—addressing a gap in existing research and providing empirical insights tailored to marginalized urban environments. Specifically, the study presents quantitative findings derived from a structured questionnaire administered to township residents.

The primary aim of this study is to examine the determinants influencing the use and acceptance of smart services in South African townships using an extended UTAUT model. he objectives of this research are: (1) to identify the key factors influencing the adoption and use of smart services, (2) to assess how the independent variables indirectly impact smart service usage through behavioral intention, and (3) to examine the effects of UTAUT moderating variables on the acceptance and utilization of smart services

2. METHODS

This study employed a quantitative research methodology to systematically examine the factors influencing smart service adoption. A structured survey was used as the primary data collection tool, and the resulting data were analyzed using Structural Equation Modelling (SEM) with SPSS and AMOS. To provide a clear overview of the research process, a diagram is included to illustrate each step—from data collection to statistical analysis—offering a visual summary of the methodological flow as depicted in Figure 1.

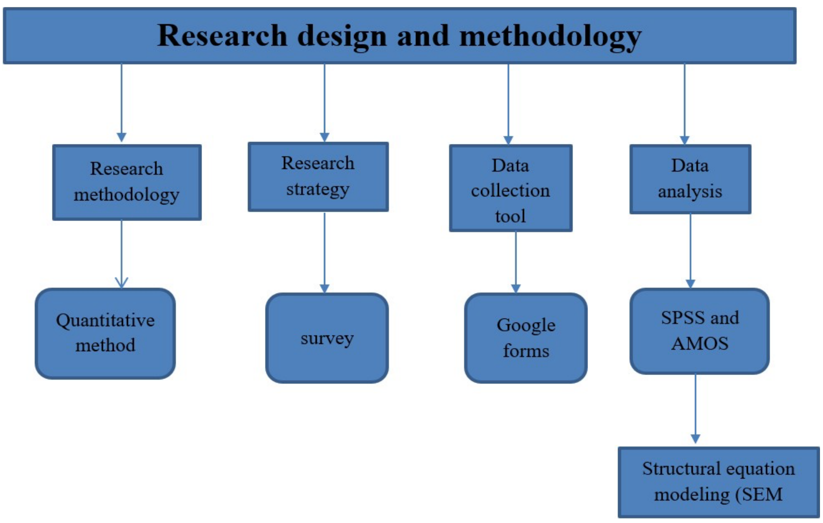

Figure 1. The research design and methodology

This study employed a quantitative research design, which is appropriate for examining measurable relationships between variables and testing theoretical assumptions. Quantitative methods enable statistical analysis, generalization of findings, and identification of patterns and trends within the target population. This design aligns with the study's objective to analyses the determinants influencing the acceptance and use of smart services in South African townships using an extended UTAUT framework.

2.1. Population and Sampling

The target population comprised residents of South African township communities, representing diverse age groups, gender categories, income levels, and educational backgrounds. A probability-based sampling approach was used to ensure that each resident had an equal chance of selection, thereby enhancing the representativeness of the sample.

To account for geographical diversity, the survey was distributed across multiple township clusters in different provinces. These clusters included high-density and low-density areas, as well as townships located near urban centers and on the peripheries. Participants were reached through community WhatsApp groups, local social media pages, ward councilor networks, and township-based organizations. This strategy ensured coverage of a broad spectrum of residents, capturing variations in infrastructure access, digital literacy, and exposure to smart services. The minimum required sample size was calculated as 382 respondents, based on a 95% confidence level with a 5% margin of error. The study exceeded this requirement, obtaining 472 valid responses, thereby enhancing the reliability and generalizability of the results.

2.2. Data analysis method

Data analysis was conducted using AMOS, an extension of SPSS designed for structural equation modeling (SEM), confirmatory factor analysis (CFA), and path analysis. CFA was employed to assess the extent to which the observed data aligned with the hypothesized constructs derived from the UTAUT model. Specifically, it was used to validate the proposed factors influencing the adoption and use of smart application services. The measurement model was developed and tested for goodness of fit, which reflects how well the proposed model explains the correlations among variables in the dataset [44]. A good model fit indicates that the proposed model adequately accounts for the observed relationships, whereas a poor fit suggests a substantial discrepancy between the hypothesized and actual correlations.

This section presents the epistemological analysis of the Unified Theory of Acceptance and Use of Technology (UTAUT) model, which underpins the conceptual foundation of this study [11]. The UTAUT model is adopted as a guiding framework because it provides a robust structure for examining technology acceptance and use, incorporating critical elements of validity, reliability, factor analysis, structural modeling, and correlation testing. Following [11] this study aligns its measurement and analysis with the methodological standards of the original model to ensure rigor and consistency. However, given the evolving technological and social context, this research extends the original UTAUT model by introducing additional constructs and moderating variables that better reflect the realities of the study setting. While the original UTAUT constructs performance expectancy, effort expectancy, social influence, and facilitating conditions remain central, three supplementary constructs have been incorporated**:** trust, perceived risk, and self-efficacy**.**

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by [11], integrates multiple technology acceptance models to explain user adoption behavior. The model identifies four key determinants of behavioral intention and usage behavior: Performance Expectancy (PE), or the extent to which residents believe smart technologies will improve their daily lives and township services; Effort Expectancy (EE), the perceived ease of using these technologies; Social Influence (SI), the degree to which users perceive that important community members or peers expect them to engage with smart systems; and Facilitating Conditions (FC), the belief that adequate infrastructure and support exist to enable technology use. These relationships are moderated by age, gender, experience, and voluntariness of use, which shape the influence of each determinant. UTAUT has been widely validated and demonstrates strong predictive power for technology adoption, making it a relevant framework for understanding the acceptance and use of smart township programmes and services.

While the original UTAUT model provides a robust framework, its explanatory power can be strengthened for densely populated urban areas and developing-country contexts by incorporating additional constructs that reflect local socio-economic and historical

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conditions. Trust is critical, as residents' willingness to adopt smart services depends on their confidence in the security, reliability, and intentions of technology providers, particularly in areas with historical governance challenges. Perceived Risk captures users' evaluation of potential negative consequences—such as financial loss, system failure, or misuse of personal data—which can be especially salient in resource-constrained communities with limited exposure to digital services. Self-Efficacy reflects individuals' confidence in their ability to use technology effectively, which varies widely in areas with diverse educational backgrounds and limited digital literacy. Integrating these constructs into the UTAUT framework provides a more comprehensive theoretical foundation, addressing socio-cultural and infrastructural factors that influence adoption and enabling a nuanced understanding of smart service acceptance in developing urban contexts.

2.3. Theoretical Framework and Constructs

This study employs constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT) and related theories to examine factors influencing the adoption of smart service applications. The independent variables and the dependent variable, Behavioral Intention, are described below.

2.3.1. Effort Expectancy (EE)

Effort Expectancy (EE) refers to the degree of ease and convenience associated with using a system [11]. In this study, EE relates to how easily users can interact with smart technologies and their associated services. Research has identified EE as a strong predictor of Behavioral Intention [11],[12],[8], although some studies report no significant effect; [13].EE can be measured using indicators that assess how easily users can interact with a system. Perceived ease of use reflects the belief that the smart service application will not be difficult to operate. Simplicity of interaction captures the perception that the application can be used easily and without unnecessary effort. These indicators together help evaluate the level of user-friendliness and accessibility of the system.

2.3.2. Social Influence (SI)

Social Influence (SI) is the degree to which an individual's decision to use a system is shaped by the perceptions of people who are important to them [11]. In this study, SI reflects the extent to which users' intentions to adopt smart service applications are influenced by the opinions and expectations of significant others. Prior research shows that SI positively affects Behavioral Intention [9],[11], [12],[14].SI can be assessed using indicators that capture the impact of social expectations on system use. Personal norm reflects the belief that one's use of the system is guided by the expectations of important individuals. Social factors represent the degree to which an individual aligns their use of smart services with cultural norms or the behaviors prevalent in their social environment. Together, these indicators provide insight into how social context shapes user adoption of smart service systems.

2.3.3. Facilitating Conditions (FC)

Facilitating Conditions (FC) refer to the extent to which individuals believe that organizational and technical infrastructure exists to support the use of a system [10]. Research shows mixed results: some studies report a significant effect on Behavioral Intention [9],[11],[12],[14], while others report no significant influence [13],[49]. Facilitating conditions can be evaluated through indicators that assess the support available for using a system. Perceptual management reflects the influence of internal and external constraints on behavior, including self-belief, resource availability, and technological support. Infrastructure support captures the extent to which access to devices, internet connectivity, and other resources enables the effective use of smart technology. Together, these indicators help determine how environmental and personal factors facilitate or hinder user adoption of smart services.

2.3.4. Self-Efficacy (SE)

Self-Efficacy (SE), derived from Social Cognitive Theory [15], is the belief in one's capability to successfully perform a specific task. It concerns the confidence in applying skills rather than possessing them, shaping how individuals think, behave, feel, and sustain motivation [8],[9],[12],[16]. Self-efficacy can be measured using indicators that assess an individual's confidence and capability in using a system. Confidence in task performance reflects the belief in one's ability to successfully operate smart technologies. Problem solving ability captures the belief in one's capacity to overcome challenges encountered while using the system. Adaptability represents the belief in one's ability to learn and adjust to new features or updates within the system. Together, these indicators provide a comprehensive understanding of how user confidence and competence influence the adoption and effective use of smart service systems.

2.3.5. Performance expectancy (PE)

According to [13], Performance Expectancy (PE) refers to the degree to which an individual believes that using a system will enhance their job performance. In the context of this study, PE reflects how residents in a smart township perceive that engaging with smart township programmes and technologies can improve the overall "smartness" of the township and enhance their daily lives. This includes the perceived usefulness of smart technologies, specifically the extent to which users believe these technologies will improve their quality of life, as well as the perceived performance benefits, referring to how system features are believed to enhance personal tasks and community-level outcomes. Prior research by [54],[11] has consistently shown that PE significantly influences Behavioral Intention (BI) in the UTAUT model. Furthermore, PE has been widely validated as a strong and continuous predictor of BI across various contexts [54],[55].

2.3.6. Perceived Risk (PR)

Perceived Risk (PR) is the combination of the seriousness of potential negative outcomes and the uncertainty associated with them [17],[18]. In information systems, it refers to potential loss or harm from system use [19],[20]. High perceived risk can reduce the perceived benefits of adopting new technology [17],[18]. Empirical findings are mixed, with some studies showing strong influence on user behavior [9],[12] and others reporting insignificant or negative effects [13],[21],[22]. Perceived risk can be evaluated through several indicators. Financial risk reflects concerns about potential monetary loss or costs associated with using the system. Privacy and security risk captures worries that personal or sensitive information may be compromised during system use. Performance risk represents apprehension that the system may not function as expected or fail to meet user needs. Together, these indicators help assess the potential barriers and uncertainties that users perceive when interacting with a system.

2.3.7. Trust (TR)

Trust is a key determinant in adopting information systems, reflecting perceptions of system reliability and integrity [23]. It encompasses the belief that the system demonstrates integrity, benevolence, and meets user expectations [24]. While most studies find a positive effect of trust on Behavioral Intention, some report inconclusive or context-dependent results [23], [25-28]. Trust in a system can be measured using several key indicators. Reliability reflects the belief that the system consistently performs as expected, ensuring users can depend on its functionality. Integrity captures the perception that the system operates honestly and ethically, adhering to principles that foster confidence. Benevolence represents the belief that the system considers users' interests and well-being, demonstrating a commitment to serving them fairly and responsibly. Together, these indicators provide a comprehensive assessment of trustworthiness in a system.

2.3.8. Behavioral Intention (BI)

Behavioral Intention refers to an individual's intention to perform a specific behavior and is commonly used to predict actual system use [9], [11],[12]. Use behavior, on the other hand, measures the real frequency and extent of system usage [13],[26]. Behavioral intention can be assessed using specific indicators. Attitude toward behavior reflects the degree to which users hold a positive or negative evaluation of using the smart service system, influencing their willingness to engage with it. Normative considerations capture the extent to which social expectations and perceived norms shape users' intention to adopt the system in the future. Together, these indicators provide insight into the factors that drive users' behavioral intentions toward smart service systems.

3. RESULTS AND DISCUSSION

3.1. Confirmatory Factor Analysis (CFA).

The following analysis evaluates the model fit for this research; firstly, an unmodified measurement model is highlighted, and a modified model fit is presented. Both measurement models highlight the main four indices of interest: RMSEA, CFI, GFI, and the chi-square. The analysis below assesses the model fit for this study, beginning with the unmodified measurement model, followed by the refined version. In both cases, four key fit indices are emphasized: RMSEA, CFI, GFI, and chi-square. Table 1 depicts the model fit threshold applied in this paper.

Table 1. Model fit threshold

Measure	Threshold	Threshold Citation
CMIN/DF	< 3.00	[45]
RMSEA	< 0.08	[46]

Measure	Threshold	Threshold Citation
CFI	> 0.90	[47]
TLI	> 0.90	[47]
p-value	< 0.05	[48]
PClose	> 0.05	[37]
SRMR	< 0.09	[37]

3.1.1. Analysis of the unmodified model fit

The unmodified model produced a CMIN value of 1.930, which is considered excessively high and therefore unacceptable. According to [40],[35], larger sample sizes tend to inflate CMIN values, and in this case, the elevated figure is likely a result of the substantial sample size. As such, CMIN should not be interpreted in isolation when assessing model fit. The CFI for the unmodified model was .893, which falls within an acceptable range but suggests that the model could be improved [29],[30]. This indicates that refinements, such as regrouping indicators under the appropriate latent variables, may enhance the model fit. The GFI was reported at .866, below the recommended threshold, further highlighting the need for adjustment [31]. By contrast, the RMSEA value was .047, which is within the acceptable range and indicates a satisfactory fit [33], [34].

3.1.2. Refined measurement model results

The chi-square value in the refined model is 1.729; it has improved though still high. The CFI value has improved from .893 to .917 in the refined measurement model. This value is within an acceptable range [29],[31]. The GFI value has improved from .866 to .882, slightly improved but still not within the value of an acceptable model fit [30],[32]. The RMSEA improved from .044 to .039, which is better and is an acceptable value indicating a stronger model fit [33],[35],[36].In the refined model, the chi-square value decreased to 1.729, reflecting an improvement, although it remained relatively high. The CFI value also increased from .893 to .917, placing it within the acceptable range [29],[37]. Similarly, the GFI value rose from .866 to .882, showing slight progress but still falling short of the recommended threshold for model fit [32]. The RMSEA improved from .044 to .039, a change that indicates an acceptable and stronger model fit [33], [36].

3.2. Construct validity of the CFA measurement model.

Table 2. presents the Construct validity of the CFA measurement model. According to [41] the cut-off value for composite reliability (CR) is 0.6; therefore, all the indices reported in the table are considered acceptable. The threshold for average variance extracted (AVE) is 0.5, and only two indices met this requirement. This shortfall may be attributed to the high correlation among the first-order latent variables. Although deleting some items could potentially improve the AVE values, this approach was avoided as it could lead to an unidentified model. In addition, removing items was not deemed appropriate, since they are theoretically grounded in the UTAUT framework guiding this study.

Table 2. Construct validity of the CFA

	CR	**AVE**
Performance expectancy	0.733	0.410
Environmental barriers	0.649	0.340
Behavioral intention	0.803	0.670
Effort expectancy	0.749	0.431
Facilitating conditions	0.730	0.410
Risk.	0.864	0.392
Self-efficacy	0.718	0.460
Social influence	0.646	0.272
Trust	0.794	0.494
Use	0.682	0.545

The low AVE values (below the recommended threshold of 0.50) indicate potential challenges with convergent validity, suggesting that some items may not adequately capture the variance of their intended constructs. Although the measurement model demonstrates acceptable internal consistency through strong Composite Reliability values, the suboptimal AVE results imply reduced precision in defining the latent variables. This limitation requires cautious interpretation of the findings. However, several scholars highlight that AVE is a conservative criterion and should not be applied rigidly. [41] argue that constructs may still be considered adequate when Composite Reliability exceeds 0.60, even if AVE falls below 0.50. Similarly, [52]note that measurement models should be evaluated holistically, rather than eliminated solely on the basis of AVE. Further, [53] emphasize that AVE is sensitive to minor measurement imperfections, and [32] suggests that practical research contexts—especially in social and behavioral

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sciences—may inevitably produce slightly lower AVE values without compromising overall model validity. Based on this literature, the model remains acceptable, but future studies should refine scale items to improve convergent validity

3.3. The structural model assessment.

A structural equation model was developed using AMOS to examine the proposed relationships. The model fit statistics were as follows: CMIN = 70.19, df = 6, CMIN/df = 11.70, standardized RMR = .0103, CFI = 1.000, RMSEA = .019, and PCLOSE = .834. These indices indicated an acceptable model fit, although improvements in the CFI were limited, as no modification indices were available [29],[31]. The squared multiple correlations revealed that behavioral intention accounted for .713 of the variances, while smart services explained .216 [32],[35]. This study further evaluated the effects of trust, social influence, self-efficacy, risk, performance expectancy, effort expectancy, facilitating conditions, and barriers on the use of smart services, in line with recent SEM applications in digital adoption research [33], [38], [39]. The direct effects of the independent variables on the dependent variable are presented in Table 1.3.

3.3.1. The hypotheses

This study examined the effects of trust, social influence, self-efficacy, perceived risk, performance expectancy, effort expectancy, facilitating conditions, and barriers on the adoption and use of smart services. Table 3 presents the direct relationships between the independent variables and the dependent variable. The findings indicate that trust, risk, social influence, facilitating conditions, and environmental barriers exert a positive influence on behavioral intention. In addition, the results reveal that environmental barriers, behavioral intention, facilitating conditions, and social expectancy have a positive effect on the actual use of smart services.

Table 3. Hypothesis

Hypothesis	Estimate	C.R.	P	Decision
H1: Trust has a positive impact on behavioral intention	,337	2,623	,009	supported
H2: Self-efficacy has a positive impact on behavioral intention	,084	1,456	,145	Not supported

Hypothesis	Estimate	C.R.	P	Decision
H3: Risk has a positive impact on behavioral intention	-,090	-3,592	***	Supported
H4: Social influence ->Behavioural intention	-,210	-3,089	,002	Supported
H5: Performance expectancy has a positive impact on behavioral intention	-,038	-,571	,568	Not supported
H6: Facilitating conditions have a positive impact on behavioral intention	,874	11,501	***	Supported
H7: Effort expectancy has a positive impact on behavioral intention	-,055	-,913	,361	Not supported
H8: Barriers have a positive impact on the use of smart services	-,196	-3,219	,001	Supported
H9: Behavioral intention has a positive impact on the use of smart services	,131	2,591	,010	Supported
H10: Facilitating conditions have a positive impact on the use of smart services	-,328	-5,559	***	Supported
H11: Social expectancy has a positive impact on the use of smart services	-,211	-4,980	***	Supported

3.3.2. Mediating hypothesis

The study further examined the mediating hypothesis to assess how the independent variables trust, social influence, risk, performance expectancy, effort expectancy, facilitating conditions and self-efficacy indirectly influence smart service usage through behavioral intention. This approach provides a deeper understanding of the mechanisms driving technology acceptance in smart townships. The mediating results indicate that behavioral intention mediates the positive effect of trust, social influence, risk, and facilitating condition.

Table 4. Mediating results

Mediating hypothesis	Estimate	P	Decision
H12: Behavioural intention mediates the positive effect of trust on the use of smart services	,044	,031	Supported

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Mediating hypothesis	Estimate	P	Decision
H13: Behavioural intention mediates the positive effect of social influence on the use of smart services	-,027	,006	Supported
H14: Behavioural intention mediates the positive effect of self-efficacy on the use of smart services	,011	,153	Not supported
H15: Behavioural intention mediates the positive effect of risk on the use of smart services	-,012	,007	Supported
H16: Behavioural intention mediates the positive effect of performance expectancy on the use of smart services	-,005	,546	Not supported
H17: Behavioural intention mediates the positive effect of effort expectancy on the use of smart services	-,007	,313	Not supported
H18: Behavioural intention mediates the positive effect of facilitating conditions on the use of smart services	,115	,009	Supported

3.3.3. The effect of moderators

This study considered education, income, age, and gender as moderating variables. To evaluate their impact on the relationships among the constructs in the proposed model, multi-group analysis was employed alongside measurement invariance testing. These procedures allowed for the assessment of whether the structural relationships were consistent or varied across the different demographic groups

1) Gender effect

The sample comprised 251 male and 221 female respondents. Consistent with the recommendations of [42][43], the final structural model was tested separately across gender groups to assess model fit. The analysis produced the following results: CMIN = 138.81, df = 12, CMIN/df = 1.157, standardized RMR = .004, CFI = .999, RMSEA = .018, and PCLOSE = .934. A comparison of the gender groups showed no significant differences in structural weights, as indicated by the non-significant p-value (p = .310), confirming invariance across male and female respondents [31],[33],[35],[39].

Table 5. The unstandardized path analysis and p-value for the gender group

Path	Males	Females	Decision
	P	P	
Behl <--- Trust	,031	,238	Path not significant for both males and females
Behl <--- SocE	,124	,638	Path not significant for both males and females
Behl <--- Risk	***	,126	Path significant for males but not for females
Behl <--- Socl	***	,740	Path significant for males but not for females
Behl <--- PerE	,505	,660	Path not significant for both males and females
Behl <--- FacC	***	***	Path significant for both males and females
Behl <--- Effort exp	,667	,099	Path not significant for both males and females
Use <--- Barries	,065	,010	Path not significant for both males and females
Use <--- Behl	,033	,098	Path not significant for both males and females
Use <--- FacC	***	,003	Path significant for both males and females
Use <--- SocE	,002	***	Path significant for both males and females

Note: Behl: behavioral intention, SocE- social expectancy- social influence, PerE-performance expectancy, FacC-facilitating conditions,*** P

2) Age effect

The descriptive frequencies for the age variable allowed the sample to be divided into four groups: 18–20, 21–30, 31–40, and 41–50. The model fit indices were as follows: CMIN = 288.07, df = 24, CMIN/df = 12.00, standardized RMR = .005, CFI = .998, RMSEA = .021, and PCLOSE = .990. These results indicated an adequate model fit. Model comparison across age groups showed that the structural weights were invariant, as reflected by the non-significant p-value (p = .377). Given the satisfactory model fit, the group analysis for factor structure equivalence was conducted simultaneously. The estimated critical ratios (t-values) and standardized coefficients are presented in Table 1.6.

Table 6. The unstandardized path analysis and p-value for the age group

Path	18-20	20-30	31-40	41-50	Decision
	p	p	p	p	
Behl <--- Trust	,375	,016	,447	,317	The path is insignificant for all age groups.
Behl <--- SocE	,325	,700	,498	,095	The path is insignificant for all age groups.
Behl <--- Risk	,388	,145	,033	,328	The path is insignificant for all age groups.

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Path	18-20	20-30	31-40	41-50	Decision
	P	P	P	P	
BehI <--- SocI	,723	,061	,006	,596	Path not significant for all the age groups except age group 31-40
BehI <--- PerE	,590	,129	,951	,903	The path is insignificant for all age groups.
BehI <--- FacC	***	***	***	***	The path is significant for all age groups.
BehI <--- Effort	,070	,772	,599	,776	The path is insignificant for all age groups.
Use<-- expBarries	,020	,376	***	,758	Path not significant for all the age groups except for age group 31-40
Use <--- Behal	,811	,251	,008	,483	The path is insignificant for all age groups.
Use <--- FacC	***	,060	***	,125	The path is not significant for the age groups 20-30 and 41-50 but significant for the age groups
Use <--- SocE	,052	,051	,009	,008	[18]The path is [-20 and 31]insignificant[-40.] for all age groups.

3) Income effect

The descriptive frequencies for the income variable were categorized into three levels: under 15,000, between 15,000 and 50,000, and between 50,000 and 100,000. Structural model estimates for all three groups produced the following fit statistics: CMIN = 286.42, df = 18, CMIN/df = 15.91, standardized RMR = .006, CFI = .996, RMSEA = .036, and PCLOSE = .822. These results indicated a good model fit. Model comparison across income groups revealed that the structural weights differed significantly between the three categories, as evidenced by the p-value ($p = .002$). The group analysis for factor structure equivalence was conducted simultaneously, with the estimated critical ratios (t-values) and standardized coefficients reported in Table 7.

Table 7. The un-standardized path analysis and p-value for income groups

Path	UR15	BTNR15-R50	BTNR50-100	Decision
	P	P	P	
Behal <--- Trust	,076	,011	,028	The path is significant for all income groups except income group under 15thousand
Behal <--- SocE	,698	,165	,713	The path could be more significant for some income groups.

Path	UR15	BTNR15-R50	BTNR50-100	Decision
	P	P	P	
Behal <--- Risk	,005	,064	,953	Path not significant for all income groups except for income group under 15 thousand
Behal <--- Socl	,060	,006	,056	Path not significant for all income groups except for income groups between 15 thousand and thousand
Behal <--- PerE	,563	,480	,008	Path not significant for all income groups except for income groups 50thousand and 100 thousand
Behal <--- FacC	***	***	***	Path significant for all income groups
Behal <--- Effort Ex	,032	,035	,119	Path significant for all income groups except income group 50 thousand and 100 thousand
Use <--- Barries	***	,562	,995	Path not significant for all income groups except income group under 15000
Use <--- Behal	,192	,005	,400	Path not significant for all income except income group between 15 thousand and 10 thousand
Use <--- FacC	***	***	,580	Path significant for all income groups except group income group 50 thousand and 100 thousand
Use <--- SocE	***	***	,148	Path not significant for all income groups

Note UR15:Under R15000

BTN R15 -R50 :Between R15000 and R50000.

BTN R50-R100 : Between R50000-R100000

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4) Education effect

The descriptive frequencies for the education variable were categorized into six levels: below Grade 12, Grade 12, Diploma, Degree, Honours, and Master's. The model fit indices were reported as follows: CMIN = 431.45, df = 42, CMIN/df = 10.27, standardized RMR = .006, CFI = −1.000, RMSEA = .007, and PCLOSE = 1.000. These results indicated an acceptable overall model fit, although the CFI suggested room for improvement. No modification indices were available to enhance the fit. A model comparison revealed that structural residuals varied across the six education groups, as evidenced by the significant p-value (p = .010). The group analysis for factor structure equivalence was conducted simultaneously, with the estimated critical ratios (t-values) and standardized coefficients presented in Table 1.8.

Table 8. The unstandardized path analysis and p-value for the education group

Path	Below grade 12	Grade12	Diploma	Degree	Honors	Masters	Decision
	P	P	P	P	P	P	
Behal <-- Trust	***	,001	,308	,485	,202	,840	The path is significant for the education group below grade 12 and the degree.
Behal <--- SocE	,703	,670	,102	-,090	,267	,789	Path not significant for all education groups
Behal <--- Risk	,502	,044	,740	-,097	-,969	,332	Path not significant for all education groups
Behal <--SocI	,889	,001	,816	-,380	-2,515	,012	Path significant for all education groups except for education groups grade 12 and diploma.
Behal <--- PerE	,011	,508	,888	-,081	,510	,610	The path is insignificant for all education groups except those below grades 12.
Behal <--- FacC	,304	***	***	,967	3,841	***	Path significant for all education groups except for education group below grade 12
Use <--- Behal	,238	,129	,007	,249	,864	,388	Path not significant for all education groups except diploma
Use <--- FacC	,046	***	***	-,517	-2,652	,008	Path significant for all education groups

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Path	Below grade 12	Grade12	Diploma	Degree	Honors	Masters	Decision
	p	p	p	p	p	p	
Use <--- SocE	,008	,001	,142	-,204	-,140	,889	Path not significant for all education groups except for education group below grade 12 and degree
Use <--- Barriers	,024	,126	***	,182	-1,224	,221	Path not significant for all education groups except for education group below grade 12 and diploma

3.4. Discussion

The current study employed Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) to evaluate the measurement and structural models underpinning the adoption of smart services. The unmodified measurement model revealed a high CMIN value (1.930), likely inflated due to the large sample size, suggesting caution in interpreting this index in isolation. The CFI (.893) and GFI (.866) indicated suboptimal model fit, whereas the RMSEA (.047) fell within the acceptable range, highlighting areas for refinement. Following model modifications, the refined measurement model demonstrated improved fit indices: CMIN decreased to 1.729, CFI increased to .917, GFI rose to .882, and RMSEA improved to .039. Although GFI remained below the recommended threshold, the overall enhancement suggests that regrouping indicators and theoretically informed adjustments improved construct validity without compromising model identification. Composite reliability values exceeded the 0.6 threshold, confirming internal consistency, while average variance extracted (AVE) fell short for some constructs, potentially due to high intercorrelations among first-order latent variables. Deleting items was avoided to preserve theoretical integrity based on the UTAUT framework.

The structural model assessment showed acceptable fit (CFI = 1.000; RMSEA = .019), with behavioural intention explaining 71.3% of the variance, and actual smart service use accounting for 21.6%. Key determinants such as trust, risk, social influence, facilitating conditions, and environmental barriers positively influenced behavioural intention, The structural model demonstrated excellent fit (CFI = 1.000; RMSEA = .019), and the predictors accounted for a substantial proportion of variance in behavioral intention (71.3%) and a moderate proportion of variance in actual smart service use (21.6%). These results are broadly consistent with the expectations of the Unified Theory of Acceptance and Use of Technology (UTAUT), which typically reports high explanatory power for behavioral intention but more modest levels for actual use [13]. The strong variance explained in this study suggests that the extended model incorporating trust, perceived risk, environmental barriers, social influence, and facilitating conditions captures the major determinants shaping intention to use smart services in township contexts. Similar UTAUT-based studies in emerging economies have also reported strong intention-level prediction when trust, contextual barriers, and risk are included [50], reinforcing the relevance of these constructs.

The findings further show that trust**,** perceived risk**,** social influence**,** facilitating conditions, and environmental barriers all positively influence behavioral intention. The positive effect of trust aligns with prior work demonstrating that trust is a central determinant of technology acceptance in environments where institutional reliability, service continuity, and privacy concerns are prominent. Similarly, the role of perceived risk as a predictor of intention supports studies showing that users in developing contexts often evaluate risk and trust simultaneously when forming adoption decisions [50]. The significant influence of social influence reflects the well-documented social pressure and community-driven adoption patterns in UTAUT and UTAUT2 research, particularly in collectivist or resource-constrained settings where peer and family opinions shape perceptions of new systems .Finally, the positive effect of facilitating conditions aligns with multiple UTAUT extensions demonstrating that infrastructure availability, support systems, and ease of access help strengthen intention and reduce uncertainty.

A noteworthy finding concerns the role of environmental barriers, which contrary to typical expectations—showed a positive relationship with behavioral intention. This pattern may indicate that users who are more aware of barriers (such as connectivity issues, cost, or lack of municipal responsiveness) may also be more motivated to adopt smart services as a way to overcome or manage those challenges. Similar interpretations have been offered in studies where contextual constraints heighten perceived value or urgency of adopting digital solutions (Koh et al., 2015). However, further investigation is needed to clarify whether this effect reflects compensatory motivation, measurement framing, or subgroup differences in how barriers are perceived. Despite the strong explanatory power of behavioral intention, the model accounted for a more modest share of variance in actual smart service use (21.6%). This gap between intention and behavior is common in technology adoption research, where actual use is influenced by additional factors such as habit, usability challenges, affordability, or inconsistent infrastructure. Prior UTAUT-based studies in developing contexts similarly highlight that even when intention is high, behavioral constraints often limit actual usage [50]. This suggests that while users may be psychologically and socially motivated to adopt smart services, structural and infrastructural limitations may still impede full behavioral engagement in township communities.

The results further revealed that environmental barriers, behavioral intention, facilitating conditions, and social expectancy significantly influenced actual smart service use, corroborating findings from prior digital adoption research. In line with the UTAUT framework, behavioral intention emerged as a strong predictor of usage behavior, reflecting the canonical link between intention and action in technology acceptance models [13]. Facilitating conditions also positively affected actual use, consistent with studies showing that perceptions of available infrastructure and support directly shape usage [11],[51]. Interestingly, the positive effect of environmental barriers on use aligns with observations in developing settings: constraints such as limited connectivity or institutional support can actually underscore the perceived value of digital solutions and motivate adoption as a means of overcoming these obstacles. Together, these findings underscore that in township or resource-constrained environments, actual smart service use is shaped not just by intention but by contextual enablers, social norms, and recognized barriers highlighting the need for technology-adoption models to explicitly integrate environmental and infrastructural determinants.

Multi-group analyses indicated that gender and age did not moderate the structural relationships, suggesting that the determinants of behavioral intention and actual smart service use operate consistently across these demographic groups. This finding aligns with several UTAUT studies reporting invariance in adoption patterns for certain contexts, particularly when core predictors such as trust, facilitating conditions, and social influence are strong determinants [11],[51] While some prior research has observed gender or age moderation in technology adoption often in relation to performance expectancy or effort expectancy other studies, especially in digital service contexts within developing countries, report minimal demographic differences, indicating that adoption behavior may be driven more by contextual and psychosocial factors than by demographic characteristics [50]. These results suggest that interventions aimed at increasing smart service adoption can be broadly applied across age and gender groups in township communities, without requiring extensive tailoring for these specific demographics.

The moderation results reveal that the influence of trust on behavioral intention differs significantly across income and education levels, highlighting the importance of socio-economic context in technology adoption within township settings. These findings suggest that individuals with higher income and education levels may place greater emphasis on trust when forming intentions to use smart services, while those with lower income or limited education may rely more on other determinants such as perceived usefulness or ease of use. This aligns with prior research indicating that socio-demographic characteristics shape how individuals evaluate technology-related risks, reliability, and institutional credibility [41]. The results therefore contribute context-specific insight by demonstrating that trust is not a uniform predictor of adoption but is instead conditioned by structural inequalities that influence access, exposure, and confidence in digital systems. This provides a meaningful addition to UTAUT literature, which recognizes the role of moderating variables but seldom examines them in socio-economically marginalized communities [52],[32]. Overall, the moderation effects strengthen the study's contribution by showing that enhancing trust alone may not drive adoption uniformly across all groups; interventions must be tailored to income and education disparities.

The findings confirm the robustness of the proposed model and highlight the importance of trust, social influence, and facilitating conditions in shaping both intention and use of smart services. The results further underscore the necessity of considering demographic and socioeconomic moderators in understanding technology adoption, aligning with contemporary UTAUT-based research in digital environments.

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4. CONCLUSION

This study investigated the determinants of smart service adoption and acceptance in South African townships, emphasizing human, cultural, and environmental dimensions. Six indicators of smart township development—Smart Mobility, Smart People, Smart Living, Smart Governance, Smart Environments, and Smart Economies—were employed to guide the analysis. Confirmatory factor analysis and structural equation modeling were conducted using SPSS and AMOS. The findings revealed that trust, risk, social influence, facilitating conditions, and environmental barriers significantly shaped adoption behavior. Path analysis further demonstrated that risk, trust, social influence, facilitating conditions, and effort expectancy served as critical moderators influencing the acceptance and utilization of smart services. Although this study offers important insights into smart service adoption in South African townships, several opportunities exist for future research to deepen and broaden the understanding of this domain. Future studies could enhance the current model by integrating additional construct such as digital literacy, perceived value, infrastructure readiness, or cultural norms to enhance explanatory power. Further studies could also apply and validate this model across different regions within South Africa or extend it to other developing countries to enable cross context comparisons and assess the generalizability of the findings. Such work would contribute to a deeper understanding of smart service adoption dynamics in diverse socio-economic environments.

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