Identification and validation of factors affecting the success of smart village services

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ABSTRACT

This study aims to explore and validate the factors that influence the performance and effectiveness of smart village services. Smart villages have become a focus for improving the quality of life of rural communities in the era of digital technology. However, there is a lack of methods to measure and evaluate the effectiveness of smart villages. We propose a holistic framework to measure and evaluate the effectiveness of smart services in smart villages. In this study, factors that influence the success of smart village effectiveness are identified. How effective the smart village services are can be understood using the information system success model approach by DeLone and McLean. This framework is expected to provide a better understanding of the effectiveness of smart village services so that people are willing to adopt the smart village service concept. In addition, this model can also be used as decision-making support for stakeholders and is expected to improve the quality of life of rural communities in a sustainable manner.

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1. INTRODUCTION

Smart villages have emerged as an effective approach to improving the quality of life in rural areas, focusing on easier access to public services, increased community engagement, and positive social and economic impacts through the utilisation of technology. Smart village is an important part of the government's efforts to improve service quality (SQ) within the overall smart village concept. Currently, various studies have begun to develop the smart village concept, which was first introduced by Viswanadham and Vedula [1]. However, research on identifying the success factors of smart village implementation still needs to be studied further. Therefore, in this study, the identification and validation of factors that affect the success of smart village service implementation will be carried out. The identification of these factors begins with previous research, which will then generalize the main factors. These factors will be validated using the DeLone and McLean approach [2]. Aljukhadar *et al.* [3] stated that factors such as reliability, speed, accuracy, ease of use, and responsiveness to consumer needs and issues should be evaluated to ensure good SQ and enhance residents' trust in adopting new concepts. Additionally, Tejedo-Romero *et al*. [4] added that community participation is also a crucial factor in adopting new concepts, particularly in the case of smart villages. High levels of community participation reflect active engagement and overall acceptance of smart village services, contributing to the success and effectiveness of smart villages as a whole. In addition to SQ, community participation and socio-economic impact are important factors in measuring the success of the smart village concept. The primary focus of socio-economic impact considers several criteria, including improved access to public services, broader economic opportunities, enhanced quality of life, and reduction of socio-economic disparities in villages. Smart village services can effectively contribute to the overall development and well-being of rural communities, resulting in positive social and economic impacts [5]. If the economic factors are fulfilled, undoubtedly service stability will be achieved, thus making the implementation of the smart village concept successful. This is because economic factors contribute to the sustainability and long-term availability of services, as well as the availability of resources for ongoing operation and maintenance [6]. Finally, user satisfaction is a key indicator of the success of smart village services. The objective is to measure the user's satisfaction with the services provided. This can be done through surveys, interviews, or other user feedback mechanisms to understand the extent to which the services meet users' needs and expectations. High levels of satisfaction indicate that smart village services effectively meet user needs and provide a positive experience [7]. This research aims to identify and validate such factors. In general, the initial section will be divided into two parts.

The first part will present the factors that influence the adoption of smart villages. According to previous research, experts suggest that the adoption factor of smart village services is the innovation of these services. Hofman *et al.* [8] said in his article that service innovation is a strategic step to strengthen the adoption factors of new services, in this case smart villages. Cahyono and Susanto [7] indicated that external factors influencing smart village adoption include IT infrastructure readiness, financing, and flexibility; transition method; citizen awareness; awareness is very useful; easy to use; quality service; effective; reliability; protect; effective; reactivity; and legal framework. To increase smart village adoption, vigorous awareness efforts emphasizing the benefits of smart villages are required. Smart village implementation, on the other hand, has more complex issues and barriers than acceptance. Kalamatianou [9] found that behavioural intention and usage intention are influenced by supporting elements such as effort expectation, performance expectation, social influence, price value, and habit, as well as inhibiting considerations such as privacy, career, and user happiness. Siskos *et al.* [10] proposed a multicriteria method to evaluate e-government, in this case smart villages, using a system with four assessment criteria grouped from four perspectives: i) infrastructure; ii) investment; iii) electronic processes; and iv) user attitudes. The value-added model is evaluated using a multicriteria ordinal regression approach by the decision-maker assessor. Tsohou *et al.* [11] proposed a reference process model for evaluating smart village services from the perspective of citizens. This model has four stages: i) problem identification, ii) requirement formulation, iii) evaluation, and iv) feedback. This concept proved useful in providing citizens with a complete overview of smart village services in a multi-case study. Riad *et al.* [12] stated that smart villages have become a global phenomenon, with governments vying to be the first to provide online services. The satisfaction of citizens and end users with smart village electronic services is critical to the achievement of smart village objectives. When designing a smart village framework, performance, cost, and user happiness should all be taken into account. Montagna [13] investigated the main elements used to evaluate specific projects based on smart village policies. These criteria provide a simple framework to determine the components that enable smart village planning for many new opportunities, such as those that affect citizens, the business environment, or other areas of government. The fundamentals are established in this work to analyze the performance of smart village measures to evaluate the advantages and benefits of a specific plan for the government and society. Pokharel *et al.* [14] described that smart village growth and maturity requirements, according to the study, should reflect changes in the host country's political, social, and environmental perspectives.

The second section will identify factors influencing the quality of smart village services. A smart village is a rural development concept that uses information and communication technology (ICT) to improve the quality of services to rural communities, with the aim of creating a more efficient, sustainable and inclusive rural environment [1]. Factors that contribute to the success of smart villages include the need to enhance innovation in technology, digitalization, energy efficiency, and the development of human resources in rural areas [15]. Li and Shang [16], added that there are at least eight main criteria that affect SQ. System quality, dependability, security, accessibility, data quality, service capability, interactivity, and responsiveness are examples of these factors. Furthermore, it was discovered that people's intention to continue using services is heavily influenced by their perceived value, which serves as an important moderator between SQ and satisfaction. As a result, SQ, service value, and user satisfaction improve. Citizens, according to Ghareeb *et al.* [17], are a factor in smart village acceptance. Important aspects that may influence citizen adoption are identified and arranged so that citizen behavior in adopting smart village services can be explained more easily. Zioło *et al.* [18] investigated the technique for order preference by similarity to ideal solutions (TOPSIS) linear ranking system is used to investigate the relationship between environmental, social, and governance (ESG) elements and the smart village development index (EGDI) in the context of smart villages. In order to provide effective smart village services, socioeconomic aspects must be considered. Furthermore, the satisfaction of users with smart village services and the availability of knowledgeable village services also plays pivotal roles. Santa *et al.* [19] described that three main factors influence end-user expectations of government services, especially The proposed model will encompass the key factors of system quality, SQ, and information quality in the context of smart village services. The proposed model will be validated by examining various smart village initiatives in Indonesia, ensuring the accuracy and impact of the identified factors in improving rural development and service effectiveness.

2. METHOD

2.1. Theoretical backgrounds

This research provides an overarching methodology to assess the success of smart village services. As a result, the identified factors were selected after a thorough examination of each identified factor dimension, verifying their appropriateness and relevance for this study. The constructs used to create a conceptual model based on previously described factors include service availability, SQ, community participation, and socio-economic and user satisfaction. This factor will be used to complete the DeLone and McLean model [2] which will later be tested for each hypothesis generated. The research model adopts constructs from DeLone and McLean’s information systems success model and extends it to include constructs and indicators from other modeling theories that are appropriate for the context of smart village implementation. DeLone and McLean’s model was developed to measure the success of an information system, in this case the implementation of a smart village. Therefore, in this study, it is adjusted to the needs in the development of the research model. Wang *et al.* [20] used the UTAUT method to show that factors such as effort expectation and favorable conditions significantly affect the willingness to use and proposal to use smart village services. In addition, the quality of smart village information, such as availability, objectivity, usefulness, confidentiality, and completeness, are important factors in promoting the use of smart village services. These findings suggest that important factors in increasing user satisfaction with smart village services are necessary efforts, favorable conditions, and quality information. Nkanata [21] explored citizen trust in smart village systems is essential to encourage their use. This effectiveness is determined by the availability of accessible and adaptive services, as well as socioeconomic aspects such as community participation and economic well-being. People tend to actively use such services, improve their quality of life, and create better socio-economic opportunities due to high effectiveness in the smart village system. Then, Idoughi and Abdelhakim [22] added that since socio-economic factors and service availability influence citizens’ effectiveness in smart village systems, the positive intention to use smart village systems increases. This is because end users expect convenience and benefits from smart village services. The quality of electronic services is critical to the success of smart village projects, which is a component that directly affects the performance of local electronic government services. Aljukhadar *et al.* [3] described seven main dimensions can be used the quality of complex smart village services. Within this context, several dimensions are encompassed, including: i) customization and engagement, ii) data accuracy and reliability, iii) support and assistance quality, iv) user-friendliness, v) website functionality and features, vi) privacy and security measures, and vii) visual appeal. Information technology services in government institutions that meet the standards of reliability, availability, speed, security, scalability, and system adaptability and follow the principles of structured and scalable infrastructure planning and design affect socio-economic aspects and community participation. Quality and reliable services can increase efficiency and productivity in economic activities. In addition, the public will feel more effectiveness and involvement in using government information technology services, which will increase active participation in government processes and improve private-public policies [23]. The index of system quality (ISQ) is a tool designed to help determine the quality of an information system by combining the concepts of system quality and information quality. Rosa’s *et al.* research used usability (ease of use) and credibility dimensions to measure ISQ. The results showed that ISQ is essential in increasing user satisfaction with smart village services. The better the system quality determined by ISQ, the higher the user satisfaction with smart village services. This shows that user satisfaction is influenced by system quality determined by ISQ, which can increase user interest and involvement in using smart village services [24]. Hence, Sitokdana [25] to improve user satisfaction, provincial governments must ensure that their smart village websites provide high-quality information and provide additional value and improve accuracy, consistency, timeliness, completeness, reliability, availability, relevance, effectiveness, and efficiency. From the previous discussion, it can be concluded that system quality is positively related to socio-economic and service availability of smart village services. Furthermore, SQ is positively related to socio-economic and community participation, and information quality is positively related to user satisfaction. By maintaining and improving the quality of systems, services, and information in smart village, the government can contribute to socio-economic development, increase community participation, and fulfill user satisfaction. Figure 1 illustrates the relationship between variables that influence each other in improving the effectiveness of smart village services.

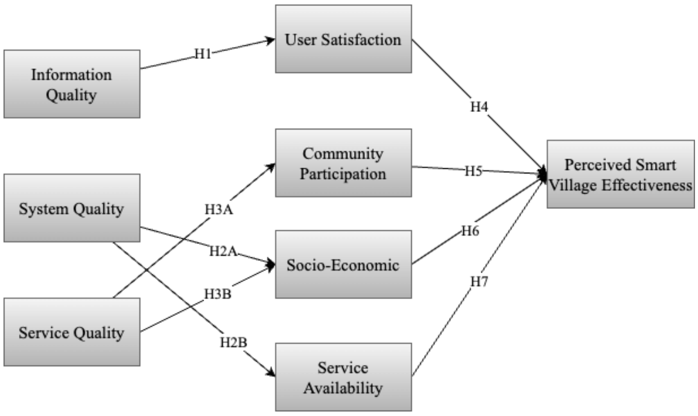

Figure 1. Perceived smart village effectiveness

DeLone and McLean [2] discovered an assumed relationship between net benefits and three quality variables: information quality, system quality, and SQ. Wang *et al.* [20] stated that enhancing system, service, and information quality is crucial to ensure the long-term acceptance and usage of smart village services. Socio-economic factors also play a role in the adoption of smart village services by residents because the anticipated benefits can improve community economics, supported by community participation [22]. Hence, community participation becomes a crucial factor in the successful implementation of smart village services [21]. From the literature review, it can be concluded that developing "system quality, information quality, and SQ" is paramount in evaluating the performance of smart village services. Additionally, user satisfaction, community participation, and the availability of socio-economic and service resources are crucial and will impact the effectiveness of innovative village services.

The hypotheses in this study, derived from the previously discussed literature and illustrated in Figure 1, posit that: information quality (H1) positively influences user satisfaction, thereby impacting the effectiveness of intelligent village services; system quality (H2a) plays a role in the efficiency of smart village services and is positively associated with socioeconomic factors; system quality (H2b) is linked to service availability, influencing the efficacy of smart village services; SQ (H3a) has a positive relationship with community participation, subsequently affecting the effectiveness of smart village services; SQ (H3b) is connected to socioeconomic factors, influencing the efficiency of smart village services; user satisfaction (H4) positively contributes to the perception of the effectiveness of intelligent village services; community participation (H5) positively contributes to the perception of the effectiveness of intelligent village services; socioeconomic factors (H6) positively contribute to the perception of the effectiveness of intelligent village services; and service availability (H7) positively contributes to the perception of the effectiveness of intelligent village services.

2.2. Research method

This empirical study utilized a quantitative analysis approach to ensure the reliability and validity of the measurement tools employed. The research process involved three key stages: conceptualizing the framework, developing the measures, and validating the framework. Hypotheses were formulated based on theoretical propositions, and variables were selected to assess the impact of these hypotheses. This research mainly focuses on quantitative data analysis to test the proposed hypotheses and evaluate the relationships between variables. This research refers to the Hair in method [26] which states that the most commonly used approaches are three approaches, namely explorative, descriptive, and causal. This research mainly adopts a descriptive approach to understanding various aspects of SQ in the smart village service. The innovative smart village services in Indonesia are utilized to verify and validate the proposed model. The Indonesian government offers a range of e-services to its citizens, and the smart village service has become one of the most widely used services by different stakeholders, including public and private sector employees and business people. The transition from smart village to smart village represents a trend in the development of public services in Indonesia.

2.2.1. The evaluation of constructs

Registration and conceptualization of each element that may be involved in the structure under study is the initial phase of this study involved the identification and evaluation of constructs including system quality, data quality, SQ, user satisfaction, socio-economic participation, and smart village service availability. A questionnaire comprising 21 items was developed to measure these variables, taking into account the findings from the literature review and feedback from participants. Iterative revisions and adjustments were made to the questionnaire during the design process before arriving at the final version. The subsequent step involves conducting an analysis of construct validity and reliability to ensure the accuracy and reliability of the collected data.

2.2.2. Sampling and gathering of data

Indonesian society has a significant variation, including education, culture, age, and skill level in using technology. Empirical data to validate the instrument and test the hypotheses was collected through a questionnaire-based survey of citizens involved in the smart village program in Indonesia. As smart village is a new initiative introduced in recent years to the community, only some residents are expected to adopt and start using the program regularly. The instrument used in this study was a questionnaire. Over a period of approximately three months, we sent out 95 questionnaires distributed to 4 main villages namely Sambirejo Village, Ponggok Village, Panggungharjo Village, and Rejosari Village. A total of ninety-five responses from the participants were collected. Responses were collected using a five-point Likert scale, from one indicating disagreement to five indicating agreement. The selection of respondents was based on village officials and villagers who were considered knowledgeable about smart village implementation. Figure 2 results of likert scale analysis from respondents.

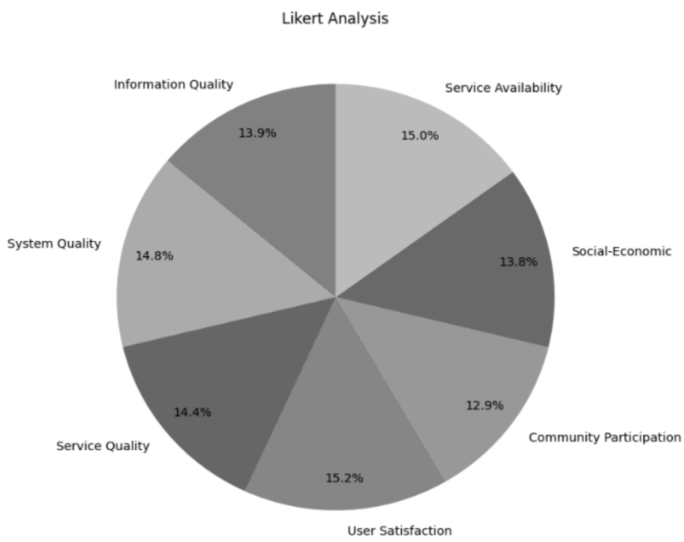

Figure 2. Likert analysis respondent

The sample size obtained was sufficient for the analysis to be conducted. About 25% of the respondents were between 24 and 45 years old, 40% were between 46 and 55, and the rest were 65 or older. Also, 68% of people who reported using smart village were male, and the other 32% were female.

3. RESULTS AND DISCUSSION

In this study, data analysis refers to Hair’s method in [26] where the first step is confirmatory factor analysis (CFA) to estimate the measurement model and assess the validity of the constructs found. Data validity and reliability are also required so that convergent and discriminant validity analysis is carried out. Then the most influential factors are identified and then testing of each factor that has been found to see the relationship between each factor.

3.1. Descriptive analysis

In this study, descriptive statistical analysis was performed to examine the normality of the data distribution. The normality of the data distribution refers to how closely the sample data aligns with a normal distribution, as explained by Hair *et al.* [27]. Table 1 shows the results of the descriptive analysis of the previously collected data.

Table 1. Descriptive statistics of the collected data are presented

Variable	Mean	Std. deviation	Skewness	Kurtosis
Information quality	3.08	0.94	-0.76	-0.33
System quality	2.82	0.90	-0.30	-0.70
SQ	3.08	0.73	-0.28	-0.60
User satisfaction	3.07	0.80	-0.37	-0.66
Community participation	2.96	0.71	-0.29	-0.05
Social economic	3.05	0.73	-0.24	-0.60
Service availability	1.81	0.99	0.90	-0.43
PSVE	3.15	0.74	-0.40	-0.59

In this study, standard deviation is used to assess the normality of variable data. A standard deviation less than 1 means that the data conforms to normal distribution. In addition, measures such as kurtosis and slope are used to measure the normality of the data. As stated by Hair *et al.* [27], the acceptable range for kurtosis is -1.5 to 1.5, and the acceptable range for skewness is -1 to 1. We can use these guidelines to check whether the variable data meet the normality assumption.

3.2. Test of reliability

We conducted a reliability analysis to evaluate the internal consistency of the measurement tool. To assess the degree of internal consistency between the items of the measurement scales, Cronbach's alpha coefficient, a widely used measure, was calculated. This coefficient indicates the degree to which items within a scale consistently measure the same construct. This coefficient provides a measure of the reliability of the scale by assessing the interrelatedness of the items and their overall consistency in measuring the construct of interest. According to Hair *et al.* [27], a widely accepted criterion for Cronbach's alpha is a value of 0.6 or higher, indicating acceptable internal consistency. However, if the value exceeds 0.9, it suggests an excellent level of association strength among the items in the measurement scale. Table 2 is the result of the reliability test with the Cronbach's alpha method.

Table 2. Cronbach's alpha value for the reliability test

Variable	Cronbach's Alpha if item deleted
Information quality	0.80
System quality	0.79
SQ	0.76
User satisfaction	0.80
Community participation	0.76
Social-economic	0.84
Service availability	0.76

Table 2 displays the results of the reliability analysis. The Cronbach's alpha coefficient for all items in each variable exceeded the 0.6 threshold, almost reaching 0.9. This finding indicates a high level of internal consistency and a strong relationship between the items and their respective variables.

3.3. Model of measurement

Positive findings from reliability testing and descriptive statistics show that the data is symmetric. 45 items were modified and analyzed in order to evaluate the performance and efficacy of smart village services. CFA was used to assess the component structures of the latent categories smart village SQ, community effectiveness, information quality, community satisfaction, system quality, usability and perceived SQ. The study of the measurement model was performed using AMOS 26 within the scope of structural equation modeling (SEM). CFA, a multivariate analysis approach, is commonly used in SEM to test model fit [27], [28]. CFA was performed on the constructions to confirm that all things loaded appropriately into their corresponding constructs. The confirmatory model produced favorable results. Various statistical indices were used to assess model fit, including standardised fit index (NFI), fit index (GFI), incremental fit index (IFI), comparative fit index (CFI), Chi-square test (χ^2), root mean residual (RMR), Tucker-Lewis index (TLI), adjusted fit index (AGFI), root mean approximation error (RMSEA) and relative Chi-square test (CMIN/DF)=(Chi-square/degrees of freedom). The GFI (.996), AGFI (.900), RMR (.029), RMSEA (.075), NFI (.997), CFI (.999), IFI (.999), TLI (.974), and CMIN/DF (1.556) all fall within acceptable ranges, indicating the model's strong fit. Table 3 presents the fit indices used to evaluate the model's fit according to the recommended criteria.

Table 3. CFA fit indices

Examination of model fit		
Fit index	Recommended range	Observed value
Measures of absolute fit		
χ2/df	≥3.00	1.556
GFI	>0.92	.996
AGFI	>0.89	.900
RMSEA	≤0.7	.075
SRMR	≤0.04	.029
Incremental model fit indicators		
CFI	>0.95	.999
TLI	>0.94	.974
IFI	>0.90	.999
NFI	>0.93	.997

3.4. Instrument's validity analysis

To assess the validity of the measurement, the validation process involved an extensive analysis of both convergent and discriminant validity. A validity analysis was performed to confirm that the constructs accurately measured the desired ideas. This involved assessing the extent to which items within each construct were converging and demonstrating high correlations with each other. Discriminant validity was also evaluated to determine whether the constructs were distinct from one another by examining the correlations between different constructs.

3.4.1. Validity converging

In this article, the authors formulate convergent criteria referring to Hair *et. al.* [27], as shown in the following Table 4. As shown in Table 4, all factor loadings, critical rates, average variance extracted (AVE), and composite reliability are within acceptable thresholds. Convergent validity refers to the extent to which two different measures of the same underlying construct are consistent and support each other. Those named Hair *et al*. [27], various ways exist to assess convergent validity. One is to ensure that the factor load (item or factor load) has a value of more than 0.55, which indicates that the degree of endorsement of the same latent variable is very high. In addition, the composite reliability should be more than 0.60, and the AVE should be more than 0.50. Cronbach's alpha coefficient, or Cronbach's alpha coefficient, should also be more than 0.70 to indicate good internal consistency. In addition, to demonstrate convergent solid validity, the critical ratio (t-value) of factor loadings should be greater than 0.70. According to Henseler *et al.* [29] convergent validity is ensured by examining the outer loading values of the indicators and determining the AVE for each construct found. The AVE itself is a summary of the convergent values calculated from the variance extracted from all elements of the construct [27]. The value limit according to Hair *et al.* [27] for the AVE value must be more than 0.50, which indicates that the indicator variance is included in the construct score. The AVE for most constructs exceeded the recommended threshold of 0.70, indicating high convergent validity. The critical ratios and factor loadings also demonstrated strong convergent validity, with most values surpassing 0.70. AVE is the sum of squares of standardized loadings divided by the sum of squares of standardized loadings and then added to the sum of indicator measurement errors. Meeting the standard criteria, the table below shows an AVE of more than 0.50 and a composite reliability of more than 0.60. The convergent validity of this study was recognized based on factor loadings, critical ratios, and AVE calculations. Based on the item/factor loading, composite reliability, AVE value calculation, T test, and critical ratio, the convergent validity test has been confirmed in this study.

Table 4. The convergent validity requirements

Integral validity source standards for recommendations	Guideline	Sources
Factor/item loading	≥0.55	Hair *et al.* [27]
Composite reliability	≥0.60	
Average variance extracted	≥0.50	
T-value for the Cronbach Alpha	≥0.70	
Coefficient critical ratio (outer loading)	≥0.70	

3.4.2. Discriminant validity

Discriminant validity is the extent to which a construct is genuinely distinct from other constructs [27]. To confirm discriminant validity, Hair *et al*. [27] suggested that the squared correlations between the components must be lower than the AVE for each construct. The results of the investigation show discriminant validity because the squared correlations, including shared variances between components, are less than the average variances of the individual constructs. Table 5 summarizes the data concerning discriminant validity. Figure 3 shows discriminant validity measurement results.

Table 5. Coefficient analysis results

Hypothesis	Variable 1	Variable 2	Coefficient	Interpretation
H1	Info qlty	User satisfaction	0.991	Very strong positive influence; higher quality information correlates with greater customer satisfaction.
H2	Sys qlty	Social economic	0.799	Favorable influence; as smart village system quality increases, community welfare tends to rise.
H3b	Svc qlty	Social economic	0.189	Positive influence; as smart village SQ increases, community well-being tends to rise, though less than Sys Qlty.
H3a	Sys qlty	Service availability	0.935	Very substantial positive influence; higher smart village system quality correlates with greater service availability.
H3b	SQ	Community involvement (CP)	0.088	Modest influence; quality of smart village services has no significant impact on village involvement.
H4	User satisfaction	Perceived smart village	-0.034	Minimal negative relationship; as user satisfaction grows, public perception of smart villages slightly decreases.
H5	Community participation	Perceived smart village	0.101	Restricted positive association; as community participation grows, people's perceptions of smart villages increase, but impact is limited.
H6	Social economic	Perceived smart village	0.282	Significant positive association; as community welfare rises, community's opinion of smart communities increases.
H7	Service availability	Perceived smart village	-0.158	Limited negative relationship; as smart village services become more available, people's impressions of smart villages slightly deteriorate.

Correlations

		InformationQuality	SystemQuality	ServiceQuality	UserSatisfaction	CommunityParticipation	SocialEconomic	ServiceAvailability
InformationQuality	Pearson Correlation	1	.991**	.982**	.991**	.090	.985**	.954**
	Sig. (1-tailed)		<,001	<,001	<,001	.194	<,001	<,001
	N	95	95	95	95	95	95	95
SystemQuality	Pearson Correlation	.991**	1	.988**	1.000**	.103	.985**	.935**
	Sig. (1-tailed)	<,001		<,001	<,001	.161	<,001	<,001
	N	95	95	95	95	95	95	95
ServiceQuality	Pearson Correlation	.982**	.988**	1	.988**	.088	.978**	.953**
	Sig. (1-tailed)	<,001	<,001		<,001	.198	<,001	<,001
	N	95	95	95	95	95	95	95
UserSatisfaction	Pearson Correlation	.991**	1.000**	.988**	1	.103	.985**	.935**
	Sig. (1-tailed)	<,001	<,001	<,001		.161	<,001	<,001
	N	95	95	95	95	95	95	95
CommunityParticipation	Pearson Correlation	.090	.103	.088	.103	1	.102	.029
	Sig. (1-tailed)	.194	.161	.198	.161		.163	.388
	N	95	95	95	95	95	95	95
SocialEconomic	Pearson Correlation	.985**	.985**	.978**	.985**	.102	1	.923**
	Sig. (1-tailed)	<,001	<,001	<,001	<,001	.163		<,001
	N	95	95	95	95	95	95	95
ServiceAvailability	Pearson Correlation	.954**	.935**	.953**	.935**	.029	.923**	1
	Sig. (1-tailed)	<,001	<,001	<,001	<,001	.388	<,001	
	N	95	95	95	95	95	95	95

**. Correlation is significant at the 0.01 level (1-tailed).

Figure 3. Measurement of discriminant validity

3.5. Structural model for analysis of hypotheses

Once the measurement model meets the criteria for model fit, the subsequent step involves constructing a structural model to examine the proposed relationships. The structural model serves as a visual representation of the underlying theory, employing a set of structural equations to depict the relationships between constructs [27]. All model fit criteria, including GFI (.915), AGFI (.883), RMSR (.068), RMSEA (0.66), NFI (.927), RFI (.914), IFI (.955), TLI (.946), and CFI (.955), fell within the acceptable range, indicating a good fit of the model. To test the provided hypotheses, the structural model was further examined by examining the standardized path coefficients, p-values, and variances for each equation inside the postulated structural model. The strength and direction of the correlations were determined using path coefficients, while t-values indicated the significance of the coefficients (t-values larger than 0.70 indicated significance levels of *** (p 0.001), ** (p 0.01), and * (p 0.05)). Additionally, the coefficient of determination (R2) was calculated for each dependent variable, providing an indication of the proportion of variance explained by the model. The path coefficient analysis results demonstrate that each variable has an effect on each other as shown in.

At the end of the table, it can be concluded that the set of hypotheses reveals diverse relationships between variables related to smart villages. Some relationships are positive and significant, such as in H1, H2, H3a, H5, and H6, while others are negative and have limited impact, such as in H4 and H7. These results provide insights into the factors that influence community perceptions and participation in the context of smart villages. Figure 4 hypothesis testing results.

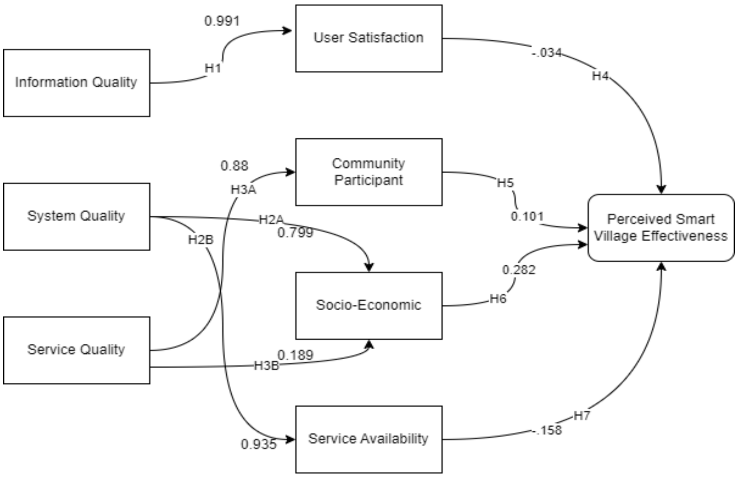

Figure 4. Results of hypothesis testing

- H1: this means: “the value of 0.991 suggests that the variable info qlty has a very strong influence on the variable user satisfaction.”
- With a coefficient of 0.991, this theory has a considerable influence, indicating a powerful influence. H2b is as follows: “the score of 0.935 suggests that the variable sys qlty has a very substantial influence on the variable service availability.”
- With a value of 0.935, this hypothesis has a large influence as well. In the meanwhile, the following hypotheses fail to satisfy the rule with a significant t-value: H3A: according to the researcher, “the value of 0.088 suggests that the variable SQ has a modest influence on the variable CP.”
- This theory has a 0.088 coefficient of effect. H4: according to the study’s authors, “the correlation coefficient value of -0.034 suggests that the user satisfaction variable and the perceived smart village variable have a negative association.”
- This hypothesis demonstrates a negative but negligible relationship with a coefficient of -0.034. H5: according to the study’s findings, “the correlation coefficient value of 0.101 suggests that the community participation variable and the perceived smart village measure have a positive association.”
- This hypothesis has a positive but insignificant relationship with a coefficient of 0.101. H6: is as follows: “the correlation coefficient value of 0.282 indicates that the social economic variable and the perceived smart village measure have a positive association.”
- With a coefficient of 0.282, this hypothesis shows a substantial positive association. H7: according to the report, “the correlation coefficient value of -0.158 suggests that the service availability variable and the perceived smart village measure have a negative association.”
- This hypothesis demonstrates a negative but insignificant relationship with a coefficient of -0.158.

4. CONCLUSION

To ensure the proper operation of a smart village, it is critical to establish integrated policies and strategies that enable the community to get high-quality services in a cost-effective and transparent manner. Smart village communities consist of individuals with diverse backgrounds and varying levels of technological literacy. Therefore, it becomes the government’s responsibility to build public effectiveness and confidence, thereby promoting widespread adoption of online services. To better understand the factors that impact the performance of smart village services, an empirical study was conducted. The study identified key components including system quality, information quality, SQ, user satisfaction, community participation, socioeconomics, and service availability. These factors combine to contribute to the effectiveness of smart village services, and the research presented in this paper highlights the importance of these elements and underlines the importance of developing and validating a framework for evaluating the performance of smart village services. Such a framework serves as a valuable tool for governments to evaluate the performance of their smart village services and gauge their overall effectiveness. This research is limited to the use of statistics to test hypotheses from a small sample. Future research can use crowdsourcing or machine learning to produce higher-quality factors

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