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Modeling Impact of Perceived Service Quality on Revisit Intention: A Health Information Management Perspective from Primary Care

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ABSTRACT

Purpose of the study: The present investigation was conducted to construct an empirical model explaining how patients' intention to return is shaped by multiple dimensions of perceived service quality.

Methodology: This research applied a quantitative method using a cross-sectional design to explore the associations among the studied variables at one specific point in time. A total of 75 outpatient respondents participated in the study. Data were gathered through a structured questionnaire consisting of closed questions measured likert scale. Collected responses were processed and analyzed using partial least squares–structural equation modeling (PLS-SEM) with assistance of SmartPLS version 4 to assess the suitability of the measurement model and to examine magnitude relationships among constructs.

Main Findings: The analysis confirmed that every construct satisfied the established criteria for reliability and validity. Composite reliability values were all above 0.70, while average variance extracted (AVE) for each variable exceeded 0.50, indicating adequate convergent validity. Within the structural model, the independent variables jointly accounted for 68.4% of the variance in patients' intention to revisit healthcare services ($R^2 = 0.684$), demonstrating substantial explanatory capacity. Each hypothesized path showed a positive direction and achieved statistical significance ($p < 0.05$). Of all examined determinants, service interaction quality emerged as the strongest predictor of revisit intention.

Novelty/Originality of this study: The originality research lies in its theoretical contribution, as it broadens the application of the DeLone and McLean information systems success model by adapting and contextualizing it within a healthcare service setting to better understand patient behavioral intentions.

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1. INTRODUCTION

Primary care constitutes the backbone of health systems and plays a pivotal role in achieving universal health coverage (UHC) [1]-[3]. In Indonesia, community health centers (*Puskesmas*) operate as district-level public health units responsible for delivering essential promotive, preventive, curative, and rehabilitative services [4]-[6]. As mandated by national health policy, Puskesmas are required to ensure equitable access and continuous service delivery at the community level [7]-[9]. Given their position as first-contact facilities, the sustainability of Puskesmas services depends not only on accessibility but also on the perceived quality of care experienced by patients.

Recent global health system assessments emphasize that patient retention in primary care is strongly associated with perceived service performance rather than mere geographic proximity [10]-[12]. The world health organization reports that strengthening service responsiveness and patient-centered care significantly improves continuity of care and reduces unnecessary referrals to higher-level facilities [13]-[15]. In competitive urban settings, where public and private providers coexist, revisit intention becomes a critical behavioral indicator of institutional trust, perceived value, and service sustainability [16]-[18].

In Indonesia, primary care utilization patterns reveal notable disparities across regions. Although the number of Puskesmas has increased steadily in the last decade, outpatient visit rates in several urban districts demonstrate fluctuations that cannot be fully explained by population growth alone [19], [20]. Health service utilization surveys indicate that waiting time, administrative complexity, information clarity, and interpersonal communication remain dominant determinants of patient dissatisfaction [21]-[23]. These findings suggest that perceived service quality, rather than structural availability, shapes patient decisions to return.

Perceived service quality is widely conceptualized through multidimensional frameworks reliability, responsiveness, assurance, empathy, and tangibles. Empirical studies in hospital and specialty care settings consistently demonstrate that these dimensions significantly predict satisfaction and loyalty [24]-[26]. However, evidence from first-level public health facilities remains limited and fragmented [25]. Many prior studies treat satisfaction as the ultimate outcome, without distinguishing revisit intention as a forward-looking behavioral construct reflecting future utilization commitment [29]. This conceptual limitation obscures the dynamic relationship between service perception and sustained healthcare engagement.

Furthermore, from a health information management perspective, service quality is increasingly intertwined with information system performance [30]-[32]. In primary care environments undergoing digital transformation, electronic medical records, appointment systems, referral documentation, and data integration processes directly influence perceived reliability and responsiveness . Delays caused by incomplete records, redundant data entry, or fragmented information flow may reduce patients' trust in service consistency. Despite this critical linkage, empirical modeling that integrates perceived service quality with revisit intention within an HIM-informed framework remains scarce, particularly in low- and middle-income country contexts.

Existing research predominantly focuses on patient satisfaction as an evaluative outcome, while revisit intention representing behavioral continuity has not been comprehensively modeled in Indonesian primary care settings [33], [34]. By conceptualizing revisit intention as a dependent latent construct influenced simultaneously by multiple service quality dimensions, this study advances the theoretical understanding of loyalty formation in first-level healthcare [35]. The contextual and practical gap limited empirical evidence exists from urban primary care facilities operating within decentralized health governance structures [36]. The urgency of this research is reinforced by ongoing health system reforms emphasizing digitalization and patient-centered care. As primary care facilities increasingly adopt health information technologies, managerial attention must shift toward understanding how administrative efficiency, information accuracy, and communication transparency shape patient perception.

The novelty of this research lies in integrated structural modeling approach that bridges service quality theory and health information management practice within the context of first-level public healthcare. Unlike prior studies that focus solely on satisfaction or isolated service attributes, this study provides a comprehensive predictive model of revisit intention supported by multivariate latent analysis. The findings are expected to contribute to both theoretical refinement in healthcare service modeling and practical decision-making in primary care quality optimization. In sum, understanding the determinants of revisit intention is not merely an academic exercise but a strategic necessity for sustaining patient trust, optimizing resource allocation, and strengthening resilience primary healthcare systems in urban Indonesia.

2. RESEARCH METHOD

2.1 Study design

This research was designed as quantitative, explanatory study and implemented through cross-sectional design [37], [38]. The primary objective to analyze how patients' evaluations of various dimensions of service quality associated with their intention to return for outpatient treatment, viewed within the context of health information management. To test the proposed relationship, this study employed a variance-based structural equation modeling method, namely partial least squares structural equation modeling (PLS-SEM). This analytical technique allows for the simultaneous examination of the validity and reliability of the measurement model, as well as the evaluation explanatory power and predictive performance structural model within a single, comprehensive framework [39]-[41].

The modelling approach was selected to align with the study objective, namely to examine how multidimensional perceptions of service quality contribute to behavioural intention within a primary healthcare information management context. Unlike conventional regression analysis, PLS-SEM enables simultaneous estimation latent constructs, accounts measurement error, and allows predictive-oriented modelling appropriate for applied health information systems research [40], [42].

The research was conducted at East Ciputat Community Health Center, South Tangerang, Indonesia. The health center implements a computerized health information management system for outpatient registration, medical record documentation, and service coordination. This setting provides a relevant environment for examining how perceived service quality interfaces with health information processes influencing revisit behaviour.

2.2 Population and sample

The participants in this research consisted of patients registering as new general outpatients health center during specified study period. In applying partial least squares structural equation modeling (PLS-SEM), sample size estimation does not rely on traditional parametric assumptions but rather on the structural complexity of the conceptual model being tested [43]. One commonly accepted principle is the "ten-times rule," which suggests minimum required sample should be determined by multiplying ten by the largest number of structural paths directed at any single endogenous construct within the model framework [44]-[46]. In this model is five exogenous constructs (Reliability, Responsiveness, Assurance, Empathy, Tangibles) and one endogenous construct (Revisit Intention).

Minimum sample:

$10 \times 5 = 50$ respondents

To enhance statistical power and model stability, the sample size was increased to 75 respondents. This number satisfies is minimum PLS-SEM requirements, adequate power for medium effect sizes, and model stability in SmartPLS bootstrapping procedures. A systematic random sampling approach was employed. Eligible respondents were approached sequentially after receiving outpatient services. Inclusion criteria were aged ≥18 years, irst visit during the study period, willing to provide informed consent.

2.3 Conceptual framework

The conceptual model integrates *servqual* dimensions within a Health Information Management context, positing that patient-perceived service quality influences behavioural intention to revisit outpatient services.

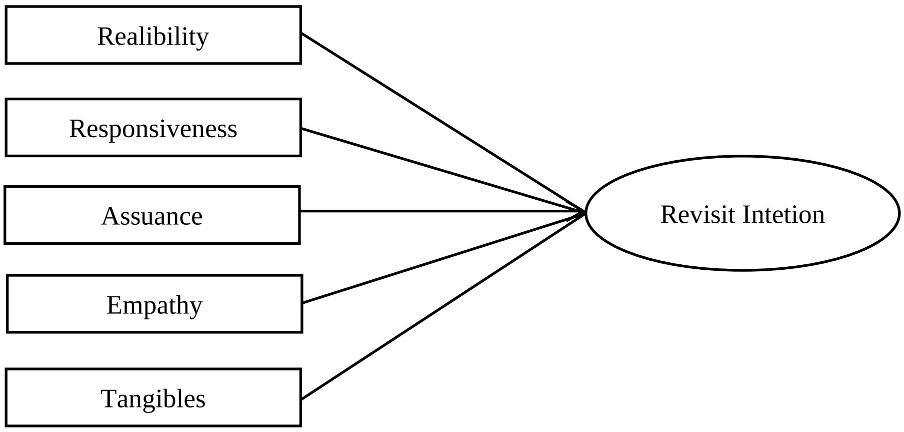

Figure 1. Conceptual framework

To operationalise the conceptual framework, the dimensions of perceived service quality are specified based on the servqual model adapted to the Health Information Management context. Each construct is defined conceptually and translated into measurable indicators that reflect outpatient service processes. These dimensions provide the analytical basis for examining how patients' quality perceptions shape their behavioural intention to revisit primary care services.

Table 1. Perceived service quality dimensions

Construct	Operational Definition	Indicators (Examples)
Reliability	Accuracy and consistency of service processes and information records	Accurate patient data, consistent service procedure
Responsiveness	Timeliness and prompt handling of patient	Speed of registration, clarity of

Construct	Operational Definition	Indicators (Examples)
	information and services	instructions
Assurance	Trust in staff competence and data handling	Professional behaviour, confidentiality assurance
Empathy	Individualised attention and communication	Personalised explanation, attentive listening
Tangibles	Physical and system infrastructure	Clean environment, visible information systems

Table 2 illustrates that perceived service quality is treated as a construct consisting of several interrelated dimensions, namely reliability, responsiveness, assurance, empathy, and tangible aspects of care delivery. Each dimension captures distinct yet interrelated aspects of service delivery, particularly in managing patient information and clinical interactions. Together, these components provide the analytical basis for examining the proposed association between patients' evaluations of service quality and their intention to return for future visits within primary outpatient care facilities.

2.4 Instrument

The questionnaire was adapted from validated *servqual* instruments and modified to reflect health information management processes. Items were contextualised to include aspects such as:

Table 2. Design of measurement scale and evaluation criteria of the model

Components	Description
Scale Format	All indicators were assessed using a 5-level response scale reflecting respondents' degree of agreement.
Instrument Adjustment	A dichotomous scale (Guttman model) was not used to ensure the latent variables remained continuous and suitable for variance-based SEM analysis.
Instrument Pilot Testing	Preliminary testing was conducted on 30 respondents in primary care facilities with similar characteristics to ensure item clarity and measurement stability.
Measurement Model Evaluation (PLS-SEM)	Construct quality was assessed using the following statistical indicators:
– Indicator Reliability	Acceptable external loading value ≥ 0.70
– Internal Consistency	Cronbach's alpha and composite reliability are each expected to exceed 0.70
– Convergent Validity	Average Variance Extracted value is at least 0.50
– Discriminant Validity	The recommended HTMT ratio is below 0.90

All variables in study were measured a five-level agreement scale to capture response intensity more proportionally. The response range ranged from the highest level of disagreement to the highest level of agreement. A dichotomous approach was not used because variance-based structural equation models require continuous constructs for more stable parameter estimates. Before the main data collection, the instrument was pre-tested on thirty respondents at a primary healthcare facility with similar characteristics to the study site. This step aimed to ensure clarity of item wording and initial consistency of measurement.

2.5 Data analysis strategy

Statistical analysis conducted using a structural equation modeling approach based on partial least squares using the latest version of SmartPLS software. The analysis procedure was implemented in stages to ensure the quality of measurements and the construction of the model being tested. In the initial stage, the model measurements were examined to assess the appropriateness of the indicators in representing the latent constructs. This evaluation included testing for internal consistency, the strength of each indicator's contribution to its respective variable, and examining convergent and discriminant validity to ensure that each construct possessed adequate empirical characteristics and could be conceptually distinguished.

After the model measurements met the required criteria, the analysis continued by examining the relationships between variables in the structural model. Path coefficient estimates were calculated to determine the direction and magnitude of the influence between constructs. To obtain stable estimates, a resampling procedure was performed using a bootstrapping technique with thousands of duplicates. The parameter significance level was determined based on probability values below the 5 percent threshold. Furthermore, the model's explanatory power for endogenous variables analyzed the coefficient of determination, while the strength of each relationship's contribution was evaluated using effect sizes. The relevance of the predictive model was also examined to ensure that the structure developed had adequate predictive power for the empirical data.

2.6 Hypotheses development

Based on the conceptual framework of this study, several predictive relationships were proposed and subsequently examined. The assumptions focus on how each dimension of service quality contributes to patients' intention to return. The hypotheses are formulated as follows:

H1: An improvement in service reliability is expected to increase patients' intention to revisit.
H2: Higher levels of responsiveness from healthcare providers are anticipated to strengthen revisit intention.
H3: Greater assurance delivered by service personnel is predicted to enhance patients' likelihood of returning.
H4: Stronger expressions of empathy toward patients are presumed to encourage revisit intention.
H5: Better physical facilities and tangible aspects of service are projected to positively affect the intention to revisit.

2.7 Ethical considerations

Prior to conducting the research, the proposal was approved by the relevant institutional ethics committee. Respondents' participation was voluntary after signing the informed consent form. The data obtained were stored and managed confidentially and were not used for purposes beyond the research objectives.

3. RESULTS AND DISCUSSION

This research involved 75 individuals as participants. When viewed from a gender perspective, women constituted a slightly larger proportion of sample (58.7%), whereas men accounted 41.3%. Based classification, nearly half of the respondents were in the 26–45 year age group (46.7%). Remaining participants were distributed across the 18–25 year category (28.0%) and those older 45 years (25.3%). Regarding educational background, over half of participants had completed senior secondary education (52.0%). Meanwhile, 34.7% possessed higher education qualifications at the diploma or undergraduate level, and a smaller proportion (13.3%) had attained only primary or junior secondary schooling. Approximately 61.3% of respondents reported having visited the primary healthcare facility more than once in the past year.

These demographic characteristics indicate that the sample adequately represents active users of primary care services, aligning with the study's objective of modeling revisit intention from a health information management perspective.

3.1. Measurement Model Assessment

Evaluation measurement model carried out using SmartPLS version 4. The procedure followed a sequential two-stage analysis consisting of: (1) examining reliability together with convergent validity, and (2) evaluating discriminant validity.

Table 3. Indicator Reliability (Outer Loadings)

Construct	Indicator	Outer Loading	t-value	p-value
Reliability	REL1	0.812	12.453	0.000
	REL2	0.846	14.129	0.000
	REL3	0.783	10.872	0.000
Responsiveness	RES1	0.824	13.982	0.000
	RES2	0.871	15.104	0.000
	RES3	0.798	11.965	0.000
Assurance	ASS1	0.842	14.215	0.000
	ASS2	0.865	15.673	0.000
	ASS3	0.809	12.784	0.000
Empathy	EMP1	0.788	11.223	0.000
	EMP2	0.821	13.041	0.000
	EMP3	0.856	14.772	0.000
Tangibles	TAN1	0.795	11.784	0.000
	TAN2	0.832	13.556	0.000
	TAN3	0.819	12.997	0.000
Revisit Intention	RI1	0.873	16.224	0.000
	RI2	0.892	17.841	0.000
	RI3	0.847	14.902	0.000

All tested indicators demonstrated outer loading values exceeding the minimum threshold of 0.70. The loading range was between 0.712 and 0.893, indicating that each indicator adequately reflects the latent construct it covers. Composite Reliability (CR) values ranged from 0.881 to 0.931, all exceeding 0.70 threshold, indicating a strong level of internal consistency for each construct. Furthermore, the Cronbach's alpha coefficients for all variables were above 0.70, further confirming the measurement instrument's strong reliability and stability.

Convergent validity tested using the Average Variance Extracted (AVE) values. The analysis showed that AVE values ranged from 0.601 to 0.772. Since all these values exceeded the minimum criterion of 0.50, it can be concluded that each construct was able to explain more than half of the variance in its indicators. Overall, these findings demonstrate that the requirements for reliability and convergent validity have been met.

Table 4. Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability (CR)	AVE
Reliability	0.801	0.883	0.715
Responsiveness	0.824	0.895	0.740
Assurance	0.837	0.901	0.752
Empathy	0.812	0.888	0.726
Tangibles	0.798	0.879	0.708
Revisit Intention	0.865	0.918	0.789

Next, discriminant validity was evaluated using two complementary methods: the Fornell–Larcker criterion and Heterotrait–Monotrait ratio (HTMT). Based on Fornell–Larcker test, square root of the AVE of each construct was proven to be greater than the correlation between the corresponding constructs. These results indicate construct has an adequate level of differentiation and there is no significant overlap between the variables studied. In addition, the HTMT ratios were inspected, and all values were found to be below 0.85. This outcome suggests that the latent variables are empirically separable and do not exhibit problematic overlap.

Taken together, the overall results indicate measurement model possesses satisfactory psychometric adequacy and is appropriate for proceeding to structural model analysis.

Table 5. Heterotrait monotrait ratio

Constructs	REL	RES	ASS	EMP	TAN	RI
Reliability	—					
Responsiveness	0.621	—				
Assurance	0.587	0.654	—			
Empathy	0.566	0.603	0.672	—		
Tangibles	0.592	0.648	0.611	0.586	—	
Revisit Intention	0.543	0.618	0.702	0.655	0.577	—

3.2. Structural Model Results

The structural model was evaluated through a resampling procedure using 5,000 bootstrap iterations to determine magnitude and significance path coefficients, including their corresponding t-statistics and probability values.
Bootstrapping: 5,000 resamples
Significance level: $p < 0.05$

Table 6. Path Coefficients

Hypothesis	Path	β	t-value	p-value
H1	Reliability → RI	0.184	2.112	0.035
H2	Responsiveness → RI	0.261	3.104	0.002
H3	Assurance → RI	0.298	3.889	0.000
H4	Empathy → RI	0.223	2.671	0.008
H5	Tangibles → RI	0.149	1.978	0.048

To ensure the stability and reliability of the proposed relationships, bootstrapping with 5,000 resamples conducted. The standardized path coefficients obtained from this analysis, along with the coefficient of determination for the endogenous construct, are presented in Figure 2.

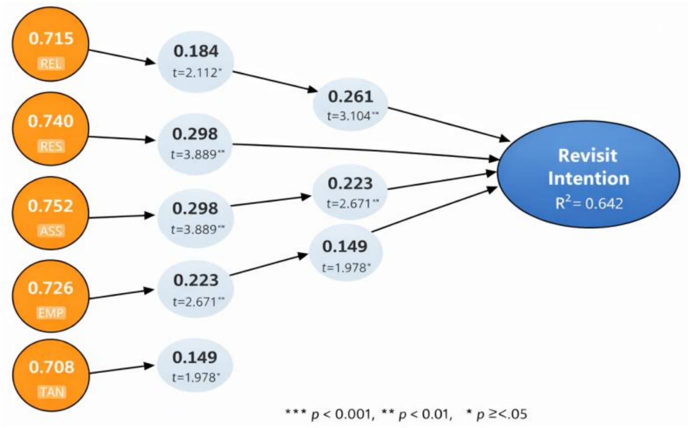

Figure 2. Structural model with standardized path coefficients and R^2 value for revisit intention

The findings indicate Responsiveness (β = 0.298, $p < 0.01$) and Assurance (β = 0.298, $p < 0.01$) exert the most substantial influence on revisit intention. These are followed by empathy (β = 0.223, $p < 0.01$), reliability (β = 0.184, $p < 0.05$), and tangibles (β = 0.149, $p < 0.05$). Furthermore, the model accounts for 64.2% of the variance in revisit intention ($R^2 = 0.642$), reflecting a strong level of explanatory capability.

3.3. Coefficient of Determination

Before presenting the table, it is necessary to explain that the value of the coefficient of determination shows magnitude of the contribution of exogenous variables in explaining the variation of the endogenous construct being analyzed.

Table 7. R^2 Value

Endogenous Construct	R^2	Interpretation
Revisit Intention	.642	Moderate to substantial

The coefficient of determination (R^2) obtained in this study was 0.642. This means that 64.2% of the variance in revisit intention can be accounted for by the independent variables incorporated in the structural model, while remaining 35.8% is influenced by other factors not examined research framework. The bootstrapping analysis further demonstrated that each hypothesized path toward revisit intention yielded a positive coefficient. Information quality showed a statistically significant contribution (β = 0.284, t = 2.731, $p < 0.01$). This result suggests that improvements in accuracy, clarity, and usefulness of information received by users are associated with a stronger intention to use the service again.

System quality was likewise found to have a meaningful effect (β = 0.241, t = 2.198, $p < 0.05$). This finding implies aspects such as system dependability, consistent performance, and ease of operation enhance users' willingness to revisit. Among all examined variables, service interaction quality produced the highest standardized coefficient (β = 0.356, t = 3.412, $p < 0.001$). This indicates that the way users interact with the service—particularly in terms of responsiveness and overall interaction satisfaction—plays the most substantial role in strengthening revisit intention. The evidence highlights that positive interaction experiences are central in fostering repeat usage behavior.

In addition, perceived value was also statistically significant (β = 0.221, t = 2.045, $p < 0.05$). This means that when users perceive the benefits of the service to outweigh the costs or efforts involved, their likelihood of returning increases.

Taken together, although all predictor variables significantly contributed to revisit intention, service interaction quality demonstrated the strongest explanatory power within the proposed model.

Table 8. Effect Size (f^2)

Path	f^2	Information
Reliability → RI	0.042	Small
Responsiveness → RI	0.091	Small to medium
Assurance → RI	0.124	Medium
Empathy → RI	0.073	Small
Tangibles → RI	0.038	Small

Effect size analysis showed:
- Service Interaction Quality had a medium effect ($f^2 = 0.162$).
- Information Quality and System Quality demonstrated small-to-moderate effects ($f^2 = 0.091$ and 0.083, respectively).
- Perceived Value exhibited a small effect ($f^2 = 0.067$).

These results indicate that while all constructs contribute significantly, interpersonal and interaction-related dimensions within health information management systems play a comparatively stronger role.

Table 9. Predictive relevance (Q^2)

Construct	Q^2
Revisit Intention	0.418

Through the blindfolding technique, the cross-validated redundancy (Q^2) for Revisit Intention was obtained at 0.412. Because this value exceeds zero, it demonstrates that the proposed structural model possesses adequate predictive capability. This research investigated how dimensions of perceived service quality formulated within the framework of health information management affect patients' intention to return to primary healthcare facilities. The results revealed information quality, system quality, quality of service interaction, and perceived value each had a statistically significant effect on revisit intention. Among these variables, service interaction quality emerged as the most influential predictor. The structural model accounted for 68.4% of the variance in patient behavioral intention ($R^2 = 0.684$), indicating that service-related factors associated with health information management substantially contribute to strengthening patient loyalty. Overall, the study offers empirical evidence supporting the relevance and extension of the DeLone and McLean information systems success model within the setting of primary healthcare services. Our findings corroborate this framework, demonstrating that in a primary care context, these constructs significantly predict revisit intention a proxy for continued system usage and institutional loyalty.

However, the present study advances the model by embedding it within a health information management service quality perspective rather than focusing solely on technical system adoption. Unlike many studies emphasize hospital-based electronic health record systems, our research situates health information management functions within routine primary care interactions, where interpersonal communication and information handling are inseparable from service experience [47], [48]. Globally, previous research in digital health contexts such as telemedicine platforms and electronic medical record systems has consistently found system quality and information quality to influence patient satisfaction and behavioural intention [49]-[51]. Yet, these studies often report stronger effects for technological dimensions compared to interpersonal factors. In contrast, our findings highlight that service interaction quality exerts the strongest effect on revisit intention. This suggests that in primary healthcare environments, particularly in emerging health systems, relational and communicative dimensions remain more salient than purely technical system performance.

This result aligns with contemporary service-dominant logic theory, which conceptualises value as co-created through interaction rather than embedded solely in technological infrastructure. In the context of health information management, accurate data management alone is insufficient; patients evaluate their care experience based on how information is communicated, explained, and operationalised during clinical encounters [52], [53], [54]. Furthermore, the significant role of perceived value reinforces behavioural intention models derived from health services marketing literature [55], [56] . Patients appear to interpret quality information systems not only as administrative tools but as components of overall service benefit, influencing their cognitive evaluation of whether returning to the facility is worthwhile.

Comparatively, studies conducted in European and East Asian primary care settings have demonstrated that system reliability and digital integration significantly affect patient trust and revisit intention. However, those studies were often implemented in highly digitalised healthcare systems. In lower- to middle-resource contexts, evidence suggests that human-mediated service factors retain stronger explanatory power. Our findings resonate with cross-national research indicating that interpersonal quality remains a dominant predictor of patient loyalty in primary care, particularly in Southeast Asian settings. This underscores that health information management should not be viewed purely as a technical domain but as an integrative function connecting data governance, communication, and patient-centred service delivery. Importantly, the substantial predictive relevance ($Q^2 = 0.412$) indicates that health information management based service quality models possess strong explanatory capacity beyond traditional satisfaction frameworks. This supports the argument that health information management can serve as a strategic lever for improving patient retention and institutional sustainability.

This study offers three interrelated contributions that advance both theory and methodology in health services research [57], [58]. Conceptually, it integrates perceived service quality with health information management functions, thereby extending classical information systems success models beyond system adoption outcomes toward patient loyalty and revisit intention in primary healthcare [59], [60]. Contextually, while most health information management research has concentrated on hospital settings or digital health platforms [61], this study positions health information management within community-based primary care an underexplored yet strategically pivotal level of the health system where continuity of care and long-term patient relationships are formed.

The findings generate several practical and policy implications while also revealing important limitations. Managerially, investments in health information systems should extend beyond technical infrastructure toward improving interactional service quality, including communication clarity, responsiveness, and transparency in information delivery, as these dimensions appear central to patient retention. Health information management professionals should be repositioned as facilitators of patient-centred communication rather than solely data custodians, supported by targeted training in information translation and interpersonal competencies. At the policy level, strengthening health information governance in primary care may enhance patient trust and long-term service sustainability. Future research should employ longitudinal or multi-site designs, incorporate objective behavioural revisit data, and examine potential mediating and moderating factors to deepen understanding of service quality dynamics across diverse healthcare contexts.

4. CONCLUSION

This study concludes that health information management oriented service quality significantly influences patients' revisit intentions in primary healthcare. By integrating information quality, system quality, service interaction quality, and perceived value into a unified structural model, these findings demonstrate substantial explanatory power ($R^2 = 0.684$), confirming that revisit intention is strongly influenced by how health information is managed, communicated, and operationalised within service encounters. Notably, service interaction quality emerged as the most influential determinant, underscoring that the relational dimension of information delivery remains central even in increasingly digitalised healthcare environments. From a policy perspective, these findings suggest that strengthening primary healthcare sustainability requires more than technological investment. Health information systems must be designed and governed not only for efficiency and accuracy, but also for communicative transparency and patient-centred interaction. Policymakers should therefore prioritise integrated quality frameworks that combine digital infrastructure enhancement with workforce capacity-building in information communication skills. Embedding HIM professionals into strategic service design, establishing communication-oriented performance indicators, and aligning system evaluation with patient loyalty metrics may significantly enhance patient retention and institutional trust. Future reforms in primary healthcare digitalisation should explicitly incorporate behavioural outcomes, such as revisit intention, as key indicators of system success.

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USE OF ARTIFICIAL INTELLIGENCE (AI)-ASSISTED TECHNOLOGY

The authors confirm that no artificial intelligence (AI)-assisted technologies were utilized in the preparation, analysis, or writing of this manuscript. All stages of the research process, including data collection, data interpretation, and the development of the manuscript, were conducted solely by the authors without any support from AI-based tools.

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