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Mobile health application adoption and service performance in Indonesian private hospitals: A JASP-compatible panel data study

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ABSTRACT

Mobile health applications have become a visible component of Indonesia's hospital digital transformation; however, management research still has limited longitudinal evidence on how hospital-level readiness factors translate into adoption and service outcomes. This manuscript presents a JASP-compatible panel data study of mobile health application adoption among Indonesian private hospitals. A balanced synthetic panel was constructed for 72 private hospitals observed over eight quarters from 2023Q1 to 2024Q4, yielding 576 hospital-quarter observations. The data structure was designed to mimic the operational indicators that private hospitals can extract from outpatient registration systems, mobile applications, customer relationship management logs, and digital governance scorecards. Linear mixed models with random intercepts were estimated for three outcomes: active mHealth use rate, patient satisfaction, and average outpatient waiting time. The results indicate that higher system quality, information quality, privacy assurance, management support, staff training, marketing support, and SATUSEHAT integration are positively associated with active mHealth use. Active use is also associated with higher patient satisfaction and shorter outpatient waiting times after controlling for service quality, hospital size, time trends, and digital integration. The findings should be interpreted as an instructional and planning-oriented demonstration rather than as evidence of identifiable hospitals because the dataset is synthetic. This study contributes a replicable IMRAD manuscript template, an APA-style reporting format, and a JASP-ready CSV file that can be replaced with real hospital panel data for journal submission or hospital management evaluation.

Keywords: mobile health; private hospitals; Indonesia; digital transformation; patient satisfaction

1. INTRODUCTION

Digital health has transitioned from an optional innovation to an operational requirement for hospitals. In Indonesia, the expansion of internet access, smartphone use, electronic medical records, platform-based telemedicine, and government-led health data integration has changed how patients search for care, register for outpatient visits, obtain clinical information, and maintain continuity with providers. Mobile health applications are especially important in private hospitals because they are at the boundary between clinical delivery and service competition. A hospital application can reduce registration friction, automate appointment reminders, display queue information, support teleconsultation, connect patients to laboratory results, and sustain patient engagement after discharge. For private providers operating in urban and semi-urban markets, the mobile channel is not only a digital health tool; it is also a service quality, brand differentiation, and patient retention mechanism (Abernethy et al., 2022; Al Aufa et al., 2020; DataReportal, 2025; World Health Organization Global Observatory for eHealth, 2011).

Indonesia is a relevant setting for studying hospital mHealth adoption because its health system combines rapid digital transformation with extensive geographic and organizational diversity. National policy has encouraged data standardization, interoperability, electronic medical records, and the SATUSEHAT platform, while the population has experienced increased access to the Internet and mobile devices. Digital transformation agenda emphasizes a connected ecosystem rather than isolated applications, and hospitals are expected to align their local systems with the national data infrastructure (Kementerian Kesehatan Republik Indonesia, 2021; Kementerian Kesehatan Republik Indonesia, 2022a; Kementerian Kesehatan Republik Indonesia, 2022b). Simultaneously, private hospitals differ widely in size, managerial capability, information system maturity, clinical service mix, and ability to invest in digital products. The same mobile application design may produce very different adoption levels depending on whether the hospital has reliable appointment workflows, trained staff, responsive customer service, and patient trust in data protection (Handayani et al., 2021; Maulana et al., 2024).

Existing Indonesian studies have provided important cross-sectional evidence of individual acceptance of mHealth and telemedicine. Research using technology acceptance and UTAUT-based perspectives has repeatedly highlighted perceived usefulness, ease of use, trust, privacy, and technology quality as drivers of the intention to use mHealth applications. Hospital teleconsultation research has also shown that user behavior and technological dimensions are relevant for technology acceptance. However, most studies treat adoption as an individual survey outcome. Few studies use hospitals as the unit of analysis, observe the same hospitals over time, and connect adoption to service performance indicators such as patient satisfaction or waiting time. This gap is important for business management because managers need to know not only whether patients like mobile applications, but also which organizational capabilities predict rising active use and whether adoption is associated with measurable service improvement (Alexandra et al., 2021; Al Aufa et al., 2020; Handayani et al., 2021; Octavius & Antonio, 2021; Salma et al., 2024).

A panel data design can contribute to this literature by allowing researchers to separate differences between hospitals from changes within hospitals over time. A private hospital with a stronger digital culture may consistently outperform others; however, a panel model can also estimate whether quarter-to-quarter improvements in system quality, staff training, integration readiness, or privacy assurance are associated with higher mHealth use. This distinction is essential from a managerial perspective. If adoption is explained mainly by stable hospital characteristics, then the strategy may require long-term investment in digital maturity and brand trust. If adoption is also responsive to within-hospital changes, managers can improve uptake through focused interventions, such as simplifying registration, increasing training, integrating application flows with call-center workflows, or communicating privacy safeguards (Bell & Jones, 2015; Bell et al., 2019).

This study develops a JASP-compatible panel data research manuscript focused on private hospitals in Indonesia. The aim was to provide a publishable IMRAD structure, an APA-style literature base, and several result tables that demonstrate how a hospital-level panel can be analyzed. This study used a synthetic balanced panel because confidential hospital records were not provided. The synthetic nature of

the data is not a weakness for this artifact's purpose; rather, it ensures privacy while providing a realistic structure that can be replaced with actual hospital data. The statistical models and results are presented as an instructional example for researchers, lecturers, and hospital managers who wish to evaluate mHealth adoption using JASP or related mixed model software (Drechsler, 2011; JASP Team, 2026).

The central research question is: Which hospital-level digital capability, service quality, and governance factors are associated with mobile health application adoption in Indonesian private hospitals, and how is adoption associated with patient satisfaction and outpatient waiting time? Three hypotheses guide the analysis. First, higher system, information, service, and privacy quality, management support, staff training, and national-platform integration were positively associated with active mHealth use. Second, higher active mHealth use was positively associated with patient satisfaction. Third, higher active mHealth use and online registration share were negatively associated with average outpatient waiting times. These hypotheses align with the technology acceptance theory, information system success theory, and service operations logic (Davis, 1989; DeLone & McLean, 2003; Betancor et al., 2025; Venkatesh et al., 2003).

The contributions of this study are threefold. Conceptually, it links technology acceptance constructs to hospital-level capabilities and service outcomes in the context of Indonesian private hospitals. Methodologically, it demonstrates a panel data approach using a structure that can be imported into JASP for mixed-model analysis. Practically, it offers managers a dashboard of adoption drivers that can support resource allocation across application design, staff training, privacy communication, and integration with the national digital health infrastructure. Because this paper is intended for an academic business-management audience, the discussion emphasizes managerial implications, research design quality, and preparation for higher-ranking journal development rather than merely reporting software output (Bell & Jones, 2015; Davis, 1989; DeLone & McLean, 2003; JASP Team, 2026; Kementerian Kesehatan Republik Indonesia, 2021).

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Technology acceptance theory provides a useful starting point for understanding mobile health adoption. The technology acceptance model argues that perceived usefulness and perceived ease of use shape behavioral intention and technology use. The unified theory of acceptance and use of technology extends this view by emphasizing performance expectancy, effort expectancy, social influence, facilitating conditions, and later, hedonic motivation, price value, and habit. In a hospital mobile application, these constructs are not only patient perceptions but also managerial design responsibilities. A patient is more likely to perceive usefulness when the application reliably solves concrete problems, such as appointment booking, queue visibility, payment preparation, laboratory result access, and clinician communication. Likewise, ease of use depends on interface quality, language clarity, loading speed, accessibility and error recovery (Al Aufa et al., 2020; Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012).

Information system success theory states that system, information, and service quality influence use and net benefits. These three dimensions are particularly suitable for private hospitals in the study. System quality refers to reliability, speed, integration, and stability. Information quality concerns whether the application provides accurate schedules, clear doctor profiles, updated queue numbers, relevant patient instructions, and reliable notifications. Service quality captures the support surrounding the application, including help desk responsiveness, staff assistance, and consistency between digital promises and in-hospital experience. A well-designed application may fail if front-desk personnel ignore online booking or if patients still need to repeat the same administrative steps upon arrival. Thus, mHealth adoption should be understood as a socio-technical service system (DeLone & McLean, 2003; Handayani et al., 2021).

Trust and privacy are also central to hospital mHealth systems. Health applications process sensitive personal information, and patient confidence can be damaged if hospitals do not communicate consent, data security, and responsible use. Indonesia's personal data protection framework and electronic medical record regulations strengthen the managerial importance of data governance. In a competitive private hospital market, privacy assurance is not merely legal compliance; it can become part of the perceived

service quality and brand credibility. Patients who believe that a hospital application protects their personal data and provides accurate information may be more willing to register, upload documents, receive notifications, or use teleconsultation features (Maulana et al., 2024; Octavius & Antonio, 2021; Republik Indonesia, 2022; Salma et al., 2024; Kementerian Kesehatan Republik Indonesia, 2022a).

The organizational aspect of adoption is equally important. Management support signals strategic priority and determines whether digital initiatives receive budgets, training, process redesign, and cross-functional coordination. Staff training is a facilitating condition because employees translate digital tools into patient experiences. If nurses, customer service officers, and outpatient administrative staff understand how to guide patients through mobile workflows, adoption barriers will decline. Conversely, if the staff view the application as extra work or are unable to resolve patient problems, digital use may remain superficial. Therefore, hospital digital capability includes not only software features but also routines, skills, incentives, and governance structures (Venkatesh et al., 2003; Weiner, 2009).

Indonesia's SATUSEHAT platform provides additional context for hospital mHealth. The platform reflects the government's efforts to integrate patient data across health facilities and standardize digital health infrastructure. For private hospitals, integration with national platforms may support interoperability, reduce duplication, and improve the legitimacy of the digital workflows. However, this integration is not automatic. Hospitals require technical interfaces, data standards, compliance readiness, and change management. The present study treated SATUSEHAT integration as a hospital-quarter indicator because the integration status can change over time and may influence active use through greater data connectivity, improved patient confidence, and better process alignment (Kementerian Kesehatan Republik Indonesia, 2021).

From a service operations perspective, mobile adoption should influence outcomes when it shifts demand management and patient flow. Online registration and appointment scheduling can reduce congestion at front desks, distribute arrival times, and lower patient uncertainty. Digital reminders may reduce missed appointments, and queue information can help patients time their arrival. Teleconsultation can substitute selected face-to-face visits, but only when triage and clinical governance are appropriate. Patient satisfaction may improve because of convenience, predictability, and perceived modernity, and waiting time may decline because of better pre-arrival processing. These effects are not guaranteed because poor implementation can simply move bottlenecks from offline counters to digital channels. Panel data can help managers evaluate whether improvements in active use are associated with measurable-service outcomes (Haleem et al., 2021; Betancor et al., 2025; Zhao et al., 2017).

Based on this literature, the first hypothesis is that hospital-level system quality, information quality, service quality, privacy assurance, management support, staff training, and SATUSEHAT integration are positively associated with the mHealth active-use rate. The second hypothesis is that the mHealth active-use rate is positively associated with patient satisfaction after controlling for service quality, privacy assurance, waiting time, hospital size, and time trends. The third hypothesis is that the mHealth active-use rate and online registration share are negatively associated with the average outpatient waiting time. These hypotheses are intentionally practical and measurable so that a private hospital can test them using its quarterly administrative records (Bell & Jones, 2015; DeLone & McLean, 2003; Davis, 1989; Venkatesh et al., 2003; Zhao et al., 2017).

3. THEORETICAL MODEL AND INDONESIAN PRIVATE HOSPITAL CONTEXT

The conceptual model integrates the TAM, UTAUT, information system success theory, and hospital service operations logic. TAM contributes perceived usefulness and ease of use, whereas UTAUT adds facilitating conditions and organizational support (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012). In this study, ease of use and usefulness were indirectly represented by hospital-level system, information, and service quality. A hospital application that reliably handles appointment booking, queue information, teleconsultation entry, and laboratory result notifications is more likely to be perceived as useful. A system that is fast, simple, and consistent with counter workflows is more likely to be perceived as easy to use by employees.

Information system success theory is especially relevant because it links technology qualities to use and net benefits (DeLone & McLean, 2003). In hospitals, net benefits may include patient convenience, waiting time reduction, better communication, improved continuity, staff efficiency, and stronger loyalty. These benefits are not produced by software alone; the application must be connected to business processes and clinical governance. For example, a queue-number feature creates value only when the outpatient unit updates the schedules in real time and honors digital appointments. A laboratory result feature creates value only when the data are released accurately and safely. Thus, this study treats mHealth as a management system embedded in hospital operations.

Indonesian evidence supports the importance of technology quality, trust, and usefulness in mobile health (mHealth) acceptance. Prior work on Indonesian mHealth users found that technological and motivational readiness, including trust and perceived usefulness, were influential readiness dimensions (Handayani et al., 2021). Another Indonesian mHealth study reported that adoption intention and recommendation intention were shaped by a combination of UTAUT2, the diffusion of innovation, and trust-related variables (Octavius & Antonio, 2021). Hospital telemedicine research similarly emphasizes user behavior and technological dimensions in the acceptance of hospital teleconsultation applications (Alexandra et al., 2021). These findings justify the translation of individual acceptance constructs into hospital-level managerial variables.

Digital transformation in Indonesia also has an institutional dimension. National initiatives, such as SATUSEHAT and electronic medical record regulations, encourage standardization and interoperability across health facilities. The World Health Organization argues that digital health strategies require the integration of financial, organizational, human, and technological resources (World Health Organization, 2021; World Health Organization, 2019). This principle is relevant for private hospitals because compliance with digital health policies cannot be separated from business strategy. A hospital that integrates digital records, trains its staff, communicates privacy safeguards, and redesigns patient flow can create a stronger mobile value proposition than a hospital that merely launches an app.

Private hospitals face strategic pressures that differ from those of public providers. They compete for patient loyalty, physician attractiveness, online reputation, corporate partnerships and service differentiation. Mobile applications can support these goals by reducing administrative friction and improving service quality before the patient arrives at the facility. However, private hospitals must also manage costs, cybersecurity risks, data governance, and unequal patient digital literacy. A digital channel that works well for younger urban patients may be less accessible for older patients or those with limited smartphone familiarity. Therefore, an adoption strategy should combine mobile services with assisted digital support in hospitals.

The research model assumes that adoption is driven by three layers of influence. The first layer is technical quality, which includes system and information quality. The second layer is organizational capability, which includes management support, staff training, and process alignment. The third layer is institutional trust, which includes privacy assurance and SATUSEHAT integration. These layers are expected to increase active use, which is expected to improve service outcomes when mobile interactions replace or streamline inefficient offline steps. Therefore, the model connects patient-facing technology with business management outcomes rather than treating mHealth adoption as a purely clinical or IT issue.

Panel data are useful for this model because private hospitals change gradually over time. A hospital may improve application reliability in one quarter, train its staff in the next quarter, and complete integration later. Cross-sectional designs would compress these processes into one observation and make it difficult to distinguish temporal changes from hospital reputation. A panel design allows researchers to examine whether changes in readiness indicators are associated with changes in adoption and service performance in the same organization. This design is also practical for management because hospitals already review many indicators on a monthly or quarterly basis. The challenge is to standardize definitions so that adoption metrics are comparable across branches and time periods.

The hypothesized pathway was not deterministic. High system quality may not generate adoption if patients are unaware of the application's existence. Marketing may not generate adoption if an app is unreliable. Privacy assurance may not matter until patients are asked to share sensitive information with

the chatbot. Although SATUSEHAT integration may improve legitimacy, it may not be visible to patients unless hospitals translate integration into smoother services. These contingencies explain why the model includes multiple predictors and why a mixed-model approach is preferred over a fixed-effects model. The purpose is not to find a single universal driver but to estimate the combined association of technical, organizational, and governance factors with adoption outcomes.

4. METHOD

This study uses a quantitative longitudinal panel design. The unit of analysis was the private hospital quarter. The panel contained synthetic observations for private hospitals in Indonesia across eight quarters from 2023Q1 to 2024Q4. A balanced panel was selected to demonstrate a clear JASP workflow and avoid complications caused by missing time periods. The synthetic dataset was calibrated to plausible ranges for Indonesian private hospital operations; however, it did not contain real patient, staff, or hospital-identifiable information. This approach allows the manuscript to present complete data management and analysis procedures while preserving confidentiality.

The hypothetical sampling frame consisted of private general and specialist hospitals located in major Indonesian provinces with active outpatient services and some form of mobile health application or digital patient portal. Hospitals were categorized by province, chain membership, and bed size of the hospital. Chain membership indicates whether a hospital belongs to a private hospital group or operates independently. Bed size was used as a proxy for the operational scale. The panel included hospitals from DKI Jakarta, West Java, Banten, Central Java, East Java, Yogyakarta, Bali, North Sumatra, and South Sulawesi to represent a mix of highly urban, peri-urban, and regional markets.

The dependent variable in the main model was the mHealth active-use rate, measured as the percentage of outpatient encounters in a quarter in which the patient used at least one meaningful mobile application function, such as appointment booking, online registration, queue checking, laboratory result access, payment preparation, or teleconsultation entry. This definition is stronger than that of simple downloads because downloads can be inflated by marketing campaigns and may not represent operational use. The active-use rate is suitable for private hospital management because it ties adoption to service delivery rather than publicity. Two additional outcomes were patient satisfaction and average outpatient waiting time. Patient satisfaction was represented on a five-point scale aggregated at the hospital-quarter level, while waiting time was measured as the average minutes between registration completion and clinical service start.

The independent variables represent the system, information, service, governance, and managerial factors. System quality, information quality, service quality, privacy assurance, and management support were measured using five-point hospital-quarter scorecards. In real research, these variables can be produced using validated questionnaires, internal audits, or quarterly digital maturity assessments. Staff training hours measured the average quarterly hours of mHealth-related training per relevant outpatient employee. Marketing spend was measured in millions of Indonesian rupiah and represented application-related patient communication, digital campaign activity, and in-hospital adoption promotion. SATUSEHAT integration was a binary variable coded once the hospital's relevant digital workflows were treated as integrated with the national platform. Online registration and teleconsultation shares measured the percentage of outpatient activity using these specific channels.

Data preparation followed a panel structure suitable for the JASP import. Each row represents one hospital in one quarter. The data included a unique hospital identifier, quarter label, numerical quarter index, grouping variables, time-varying predictors, and outcome variables. The dataset was saved in the CSV format. In JASP, the hospital identifier should be assigned as a nominal grouping variable, the quarter index as a scale or ordinal time variable, binary indicators as nominal variables, and outcome/predictor scores as scale variables. The mixed-model analysis can then specify the hospital identifier as a random-intercept grouping factor. This structure also allows researchers to produce descriptive statistics, correlation matrices, and line plots before the modelling (see Table 1).

Table 1. Panel Structure and Operational Definitions

Variable	Type	Operational definition
hospital_id	Nominal	Unique private hospital identifiers were used as panel grouping variables.
quarter / quarter_index	Time	Quarter label and numerical time trend from 1–8.
mhealth_active_use_rate	Scale	Percentage of outpatient encounters with meaningful mobile app use.
system_quality	Scale	Reliability, speed, usability, and technical stability of the hospital app.
information_quality	Scale	Accuracy and usefulness of doctor schedules, queue information, reminders, and service instructions.
service_quality	Scale	Support quality surrounding app use, including help desks and front-office consistency.
privacy_assurance	Scale	Perceived strength of privacy communication, consent, and data protection practices.
management_support	Scale	Leadership commitment, resource allocation, and cross-functional coordination.
staff_training_hours	Scale	Average quarterly training hours for staff involved in digital outpatient workflow.
satusehat_integrated	Nominal	Indicator of integration with the national digital health infrastructure in a given quarter.
patient_satisfaction	Scale	Hospital-quarter average satisfaction on a five-point scale.
avg_wait_time_minutes	Scale	Average outpatient waiting time (minutes).

Note: The dataset is synthetic and intended as a JASP-ready template for private hospital panel analyses.

The primary statistical approach was linear mixed modeling with random hospital intercepts. Random intercepts account for unobserved, time-invariant hospital characteristics, such as brand reputation, managerial culture, location attractiveness, legacy information systems, and patient socioeconomic profiles. The main adoption model regressed the mHealth active-use rate on the quarterly trend, bed size, chain membership, marketing spend, system quality, information quality, service quality, privacy assurance, management support, staff training hours, and SATUSEHAT integration. Model comparison was conducted using a time-only baseline model, a control model, and a full adoption model. This sequence indicates how much the model fit improves after adding operational and governance factors.

Two secondary mixed models were used to assess the service outcomes. The patient satisfaction model regressed satisfaction on the mHealth active-use rate, service quality, privacy assurance, average waiting time, bed size, and quarter trend. The waiting time model regressed the average outpatient waiting time on the active-use rate, online registration share, SATUSEHAT integration, staff training, bed size, and quarterly trends. The direction and significance of the coefficients were interpreted in light of the hypotheses. Because the data were synthetic, p-values and confidence intervals were used to demonstrate the reporting format rather than to infer the population truth about Indonesian hospitals.

The requested software environment was the JASP. The CSV file accompanying this manuscript can be imported directly into JASP, and Appendix A provides the exact steps for reproducing the descriptive statistics, correlations, and mixed models. The calculations in this generated version were reproduced programmatically because the execution environment used to create the Word artifact did not include the JASP desktop application. To maintain transparency, the manuscript describes the workflow as JASP-compatible and reports tables in a JASP-style APA format. When real data are available, researchers should run the analyses directly in JASP, export the output tables, and update the Results section accordingly.

Ethical considerations are minimal for the present synthetic dataset because no real patient, staff, or hospital data were included. For a real private hospital study, ethics approval or institutional review determination would be required if patient-level data, identifiable staff responses, or non-public hospital performance data were used. Data should be aggregated to the hospital-quarter level whenever possible, and patient identifiers should be removed before the analysis. Researchers should also document the legal bases for processing, data retention, access controls, and reporting safeguards in line with Indonesian privacy regulations and hospital governance policies.

For a real hospital study, data quality requires a formal data dictionary and audit trail. Each variable had a stable definition across quarters and hospitals. For example, active use should not mix downloads, logins, and completed service transactions unless these indicators are explicitly separated. Satisfaction scores should be collected using a consistent survey instrument and sampling approach, and waiting time should be extracted from the same operational timestamp definitions across facilities. Without this discipline, the panel coefficients may reflect measurement inconsistency rather than true managerial relationships.

Measurement validity is particularly important for scorecard variables such as system, information, service, and privacy assurance quality, and management support. Researchers should ideally use multi-item scales adapted from established technology acceptance and information system success literature and then test reliability before aggregation. If hospitals prefer internal audit scores, the scoring rubric should be standardized, raters trained, and inter-rater consistency checked. A high-ranking journal would expect evidence that the constructs are not arbitrary managerial labels but defensible operationalizations of theory-driven concepts.

Several robustness checks are recommended before using the model for journal submissions. First, researchers should estimate hospital fixed-effects models to examine whether the results are consistent when all time-invariant hospital differences are absorbed. Second, lagged predictors can test whether improvements in training, privacy assurance, or system quality precede adoption, rather than merely moving together in the same quarter. Third, sensitivity tests should examine whether the results differ by province, chain membership, hospital size, and baseline digital maturity. Fourth, nonlinear effects should be considered because adoption benefits may plateau once most outpatients use digital channels.

Missing data are also likely to be present in real hospital panels. System downtime, incomplete survey responses, merger activity, new branches, and changes in application vendors can create unbalanced datasets. JASP can handle many common analyses with complete cases; however, researchers should report the extent and pattern of missingness and consider multiple imputation or full-information approaches when appropriate. If missingness is related to digital maturity, simply dropping incomplete observations may result in biased results. For this reason, the synthetic dataset is balanced for instructional clarity, but the manuscript flags the missing-data strategy as a necessary step for empirical publication.

5. RESULTS AND DISCUSSION

5.1. Results

The synthetic panel contained a balanced set of hospital quarter observations. Across all quarters, the mean mHealth active-use rate was 64.6% (SD = 12.7), the mean online registration share was 55.7%, the average patient satisfaction was 3.95 on a five-point scale, and the average waiting time was 48.4 minutes. These values indicate a mid-adoption environment: mobile channels were already operational but had not replaced conventional outpatient service processes. This is consistent with the private hospital sector, in which digital services are expanding, but implementation maturity varies across organizations (see Table 2).

Table 2. Descriptive Statistics for Hospital-Quarter Variables

Variable	N	Mean	SD	Min	Max
mHealth active-use rate (%)	576	64.63	12.75	30.12	86.00
Online registration share (%)	576	55.73	16.36	14.83	90.79
Teleconsultation share (%)	576	13.20	7.62	1.83	51.66
System quality (1-5)	576	3.94	0.47	2.74	5.00
Information quality (1-5)	576	3.73	0.50	2.33	5.00
Service quality (1-5)	576	3.69	0.47	2.37	5.00
Privacy assurance (1-5)	576	3.88	0.49	2.51	5.00
Management support (1-5)	576	3.76	0.54	1.99	5.00
Staff training hours	576	15.12	3.32	4.89	24.18
Marketing spend (million IDR)	576	86.76	23.52	19.17	168.64

Average waiting time (minutes)	576	48.43	11.66	12.00	86.37
Patient satisfaction (1-5)	576	3.95	0.35	2.97	4.90
Repeat visit rate (%)	576	47.85	5.86	30.41	63.09
Complaints per 1,000 visits	576	12.69	2.28	5.58	19.73

Note: N = 576 hospital-quarter observations across 72 hospitals and eight quarters.

Quarterly trends suggest a gradual increase in digital adoption in the sector. The mean active use rose from 53.0% in 2023Q1 to 74.7% in 2024Q4. The share of hospital-quarter observations coded as SATUSEHAT integrated also increased over the study window, reaching 93.1% by the final quarter. This increase should be interpreted as a generated pattern rather than a factual national estimate; however, it demonstrates how a real hospital panel could capture policy-driven integration over time (see Table 3).

Table 3. Quarterly Trend in Adoption and Service Indicators

Quarter	Active use (%)	Online registration (%)	Satisfaction	Waiting time	SATUSEHAT integrated (%)
2023Q1	53.00	37.57	3.66	57.77	5.56
2023Q2	56.50	42.49	3.72	57.73	26.39
2023Q3	60.07	47.09	3.84	52.82	41.67
2023Q4	63.74	55.72	3.91	48.87	56.94
2024Q1	66.94	59.48	3.99	47.07	62.50
2024Q2	70.49	63.94	4.07	43.99	79.17
2024Q3	71.69	67.33	4.17	41.10	88.89
2024Q4	74.65	72.24	4.22	38.08	93.06

Note: SATUSEHAT integration is expressed as the percentage of hospitals integrated in each quarter within the synthetic panel.

Correlation results showed that active mHealth use was positively associated with system, information, and service quality, privacy assurance, management support, online registration share, and patient satisfaction, and negatively associated with waiting time. The strongest positive correlations were with system quality and online registration share, suggesting that adoption is linked to both application reliability and the embedding of mobile workflows into the appointment processes. Waiting time was negatively correlated with active use and online registration share, supporting the operational assumption that digital pre-registration can reduce front-office congestion when it is properly implemented (see Table 4).

Table 4. Pearson Correlation Matrix for Key Variables

Variable	Active use	System quality	Info quality	Service quality	Privacy	Mgmt support	Online reg	Satisfaction	Waiting
mHealth active-use rate (%)	1.00	0.64	0.63	0.54	0.62	0.57	0.74	0.80	-0.65
System quality (1-5)	0.64	1.00	0.64	0.60	0.59	0.61	0.74	0.58	-0.58
Information quality (1-5)	0.63	0.64	1.00	0.58	0.61	0.60	0.59	0.54	-0.47
Service quality (1-5)	0.54	0.60	0.58	1.00	0.54	0.56	0.60	0.57	-0.43
Privacy assurance (1-5)	0.62	0.59	0.61	0.54	1.00	0.55	0.66	0.61	-0.52
Management support (1-5)	0.57	0.61	0.60	0.56	0.55	1.00	0.56	0.50	-0.45
Online registration share (%)	0.74	0.74	0.59	0.60	0.66	0.56	1.00	0.71	-0.76

Patient satisfaction (1-5)	0.80	0.58	0.54	0.57	0.61	0.50	0.71	1.00	-0.67
Average waiting time (minutes)	-0.65	-0.58	-0.47	-0.43	-0.52	-0.45	-0.76	-0.67	1.00

Note: The correlation coefficients are based on hospital-quarter observations. The table is intended for preliminary diagnosis before mixed modeling.

Model comparison favored the full-adoption model. The time-only baseline accounted for the common upward trend but left a substantial between-hospital heterogeneity. Adding controls for hospital size, chain membership, and marketing improved the model fit. The full model, which added system quality, information quality, service quality, privacy assurance, management support, staff training, and SATUSEHAT integration, further improved the AIC and log likelihood. The null-model intraclass correlation for active use was 0.42, indicating that a meaningful share of variation was located between hospitals and that mixed modeling was appropriate for the panel structure (see Table 5).

Table 5. Model Fit Comparison for Mixed Models Predicting mHealth Active-Use Rate

Model	Fixed effects	AIC	BIC	Log likelihood	Residual variance
Time-only baseline	2	3909.71	3927.14	-1950.86	35.71
Controls	5	3890.50	3920.99	-1938.25	35.08
Full adoption model	12	3693.55	3754.53	-1832.77	26.22

Note: Models used hospital random intercepts and maximum likelihood estimation. The null-model ICC for active use was 0.42.

In the full mixed model, system quality was positively associated with the mHealth active-use rate ($B = 5.47$, $p < .001$). Privacy assurance was also positive ($B = 1.40$, $p = .045$), and SATUSEHAT integration was associated with higher active use ($B = 4.26$, $p < .001$). The positive coefficient for system quality means that a one-point improvement on the five-point system quality scorecard is associated with several additional percentage points of active mobile use, holding other factors constant. The positive privacy coefficient indicates that adoption is not solely a convenience phenomenon; trust in data handling is important for hospital digital channels (see Table 6).

Table 6. Linear Mixed Model Predicting mHealth Active-Use Rate

Predictor	B	SE	z	p	95% CI LL	95% CI UL
Intercept	-11.310	8.250	-1.371	.170	-27.480	4.860
Quarter trend	1.490	0.166	8.982	< .001	1.165	1.815
Log beds	-0.931	1.598	-0.583	.560	-4.064	2.201
Private chain group	0.547	1.355	0.404	.686	-2.109	3.204
Marketing spend (million IDR)	0.046	0.013	3.513	< .001	0.020	0.072
System quality	5.468	0.766	7.133	< .001	3.965	6.970
Information quality	4.597	0.714	6.442	< .001	3.199	5.996
Service quality	3.281	0.669	4.902	< .001	1.969	4.593
Privacy assurance	1.404	0.700	2.005	.045	0.032	2.776
Management support	2.586	0.609	4.243	< .001	1.392	3.780
Staff training hours	0.090	0.091	0.989	.323	-0.088	0.269
SATUSEHAT integrated	4.258	0.717	5.941	< .001	2.853	5.662

Note: Dependent variable: mHealth active use rate. The hospital ID was specified as a random-intercept grouping factor.

The patient satisfaction model supported the second hypothesis. Active mHealth use was positively associated with satisfaction (B = 0.013, p < .001) after adjusting for service quality, privacy assurance, waiting time, hospital size, and quarterly trends. The coefficient is modest at the one-percentage-point level, but a hospital increasing active use by 20 pp would be expected to improve satisfaction by roughly 0.27 points on a five-point scale, all else equal. In service management, this is meaningful because patient satisfaction scores often move slowly and are influenced by many non-digital factors (see Table 7).

Table 7. Linear Mixed Model Predicting Patient Satisfaction

Predictor	B	SE	z	p	95% CI LL	95% CI UL
Intercept	2.663	0.149	17.828	< .001	2.371	2.956
Quarter trend	0.015	0.005	3.225	.001	0.006	0.024
Log beds	-0.011	0.020	-0.567	.570	-0.050	0.028
mHealth active-use rate	0.013	0.001	13.577	< .001	0.011	0.015
Service quality	0.130	0.022	5.952	< .001	0.087	0.172
Privacy assurance	0.053	0.022	2.379	.017	0.009	0.096
Average waiting time	-0.006	0.001	-5.754	< .001	-0.007	-0.004

Note: Dependent variable: patient satisfaction on a five-point scale. The coefficients indicate the expected change in satisfaction, holding other variables constant.

The waiting time model supports the third hypothesis. Active mHealth use was negatively associated with average waiting time (B = -0.13, p = .001), and online registration share also had a negative association. This pattern suggests that mobile use is most valuable when it is connected to pre-arrival registration and queue-management processes. SATUSEHAT integration and staff training also displayed negative coefficients, indicating that interoperability and employee capability may support a smoother patient flow. Again, these results are illustrative because the data are synthetic, but they show what the evidence would look like if private hospitals collected comparable quarterly data (see Table 8).

Table 8. Linear Mixed Model Predicting Average Outpatient Waiting Time

Predictor	B	SE	z	p	95% CI LL	95% CI UL
Intercept	87.166	4.033	21.613	< .001	79.261	95.071
Quarter trend	-0.231	0.214	-1.078	.281	-0.651	0.189
Log beds	-0.925	0.784	-1.180	.238	-2.462	0.612
mHealth active-use rate	-0.127	0.039	-3.282	.001	-0.203	-0.051
Online registration share	-0.396	0.034	-11.803	< .001	-0.461	-0.330
SATUSEHAT integrated	-2.252	0.816	-2.759	.006	-3.853	-0.652
Staff training hours	-0.098	0.118	-0.827	.408	-0.329	0.134

Note: The dependent variable is the average outpatient waiting time in minutes. Negative coefficients indicate a shorter waiting time.

A quartile comparison reinforces this managerial interpretation. Hospitals in the highest adoption quartile had higher average satisfaction, shorter waiting times, higher repeat visit rates, and fewer complaints than those in the lowest adoption quartile. This comparison should not be interpreted causally because hospitals in the highest quartile may differ in unmeasured ways; however, it provides a useful communication tool for executives. Quartile tables can help translate mixed-model coefficients into a dashboard format that management teams understand (see Table 9 and Table 10).

Table 9. Hospital-level Comparison by Adoption Quartile

Adoption quartile	Hospitals	Active use (%)	Satisfaction	Waiting time	Repeat visits (%)	Complaints per 1,000
Q1 lowest	18	52.85	3.71	53.97	44.74	14.00
Q2	18	61.80	3.86	50.16	46.29	12.79
Q3	18	67.98	4.04	47.03	49.13	12.36
Q4 highest	18	75.91	4.18	42.56	51.24	11.60

Note: Quartiles were calculated from each hospital's mean active-use rate across all quarters; this descriptive table is not a causal estimate.

Table 10. Province-level Descriptive Profile in the Synthetic Panel

Province	Hospitals	Active use (%)	SATUSEHAT integrated (%)	Satisfaction	Waiting time
Bali	7	70.16	78.57	4.05	47.62
Banten	8	69.39	71.88	4.01	44.94
South Sulawesi	5	68.71	65.00	4.00	48.46
North Sumatra	5	68.16	47.50	4.04	44.15
Yogyakarta	2	63.54	56.25	3.91	50.30
Central Java	13	63.54	59.62	3.94	49.23
East Java	12	63.23	53.12	3.92	49.69
DKI Jakarta	10	62.79	40.00	3.93	48.15
West Java	10	58.32	47.50	3.82	51.26

Note: Province-level summaries are included to demonstrate reporting structure and should not be interpreted as factual provincial estimates.

5.2. Discussion

The results suggest that mHealth adoption in private hospitals should be managed as an integrated service transformation rather than a narrow application launch project. System quality emerged as a prominent adoption driver, which is consistent with information-system success theory and with practical hospital experience. Patients are unlikely to repeatedly use an application that is slow, inconsistent with counter workflows, or unable to complete high-value tasks. Therefore, private hospitals should prioritize stability, integration, and task completion before investing heavily in promotional campaigns. Marketing may attract patients to the application, but system quality determines whether they continue to use it (Al Aufa et al., 2020; DeLone & McLean, 2003; Handayani et al., 2021).

Privacy assurance was also positively associated with active use. This finding is important for Indonesian private hospitals because health data are sensitive, and mobile applications often require account creation, identity verification, medical record access, payment information, and notification permissions. Hospitals should communicate privacy safeguards in plain language, provide visible consent processes, train staff to answer patient questions, and align application governance with legal and professional standards to protect patient privacy. Privacy should not be hidden in lengthy terms and conditions documents. In trust-sensitive services, such as healthcare, privacy assurance is part of the value proposition (Maulana et al., 2024; Republik Indonesia, 2022; Salma et al., 2024; Kementerian Kesehatan Republik Indonesia, 2022b).

Management support and staff training are managerial levers that can be implemented immediately. A hospital may purchase or develop a technically capable application, but adoption will stall if outpatient staff continue to treat digital users as exceptions. Staff need to understand the end-to-end process: how patients book, how digital queue numbers are generated, how changes in doctor schedules are communicated, how complaints are escalated, and how teleconsultation requests are triaged. Training also reduces employee resistance because it clarifies roles and reduces anxiety regarding workflow changes. For private hospital groups, standardized training modules can create adoption routines across branches while allowing for local customization (Venkatesh et al., 2003; Weiner, 2009).

The positive association between SATUSEHAT integration and active use should be interpreted cautiously because synthetic data cannot prove a national platform effect. Nevertheless, this direction is theoretically plausible. Integration can increase the credibility of digital workflows, reduce fragmentation, and support the continuity of information. Private hospitals should view national integration not merely as compliance but as part of the patient experience. When integration improves data accuracy, reduces repeated form filling, and supports smoother transitions across facilities, patients may perceive digital channels as more useful. However, integration also requires data quality, governance, and technical maintenance; poor integration can create errors that undermine trust (Kementerian Kesehatan Republik Indonesia, 2021).

The association between active use and patient satisfaction shows that mHealth can contribute to perceived service quality when it reduces effort and uncertainty. Patients often evaluate hospitals not only based on clinical outcomes but also on the administrative journey surrounding care. Mobile applications can produce visible benefits in the areas of registration, queuing, payment, communication, and follow-up. A small improvement in satisfaction at the hospital-quarter level can have strategic value in competitive private markets because satisfaction influences word-of-mouth, online reviews, loyalty, and willingness to choose the same provider again (Bruce et al., 2020; Cao et al., 2022; Darwin et al., 2023).

The negative association between active use and waiting time highlights key operational mechanisms. Digital transformation produces value when it alters patient flow. Online appointment booking, pre-registration, queue visibility, and digital document submission can shift work from crowded counters to pre-arrival processes. However, hospitals must redesign offline workflows to accommodate digital inputs. If patients still have to repeat registration upon arrival, the application becomes symbolic rather than operational. Therefore, managers should map the patient journey and remove duplicate steps. Measures such as digital check-in kiosks, dedicated counters for online registrants, automated insurance verification, and real-time queue updates can convert mobile adoption into lower waiting times (Betancor et al., 2025; Ye et al., 2022; Zhao et al., 2017).

For researchers, this study demonstrates the value of panel data in hospital digital transformation research. Cross-sectional surveys are useful for measuring perceptions, but they cannot fully separate stable hospital differences from changes within hospitals. Panel models can be used to examine whether adoption rises after training, integration, quality improvement, or service redesign. They also allow for lagged models, moderation analysis, and intervention evaluation. Future studies could extend the present design by adding patient-level survey data, physician adoption data, cost indicators, clinical service lines, or competitive-market measures. Researchers could also compare private and public hospitals or examine differences between hospital chains and independent providers (Bell & Jones, 2015; Bell et al., 2019; Murray et al., 2016).

For journal development, the manuscript should be strengthened with real data, validated scales, and rigorous causal identification. A high-ranking journal would expect clear sampling procedures, institutional approvals, reliability and validity evidence for scorecard measures, missing data handling, sensitivity analysis, and transparent reproducibility files. If real hospital panels include staggered digital interventions, researchers can use difference-in-differences, fixed-effects models, or interrupted time-series designs. If patient-level surveys are linked to hospital-level adoption, multilevel structural equation modeling can be used to test cross-level mediation. This study provides a foundation, but publication-quality claims require real, audited, and ethically governed data (Bell & Jones, 2015; Bernal et al., 2017; Murray et al., 2016; Preacher et al., 2010).

A practical recommendation for private hospital executives is to manage mHealth adoption through a balanced scorecard. The scorecard should include the active-use rate, online registration share, task completion rate, app error rate, patient satisfaction, waiting time, complaint rate, staff training completion, privacy incidents, and integration status. Executives should review these metrics quarterly and compare branches using both absolute levels and improvement trends. High-performing hospitals can be studied as internal benchmarks, whereas low-performing hospitals can receive targeted support. This managerial process transforms mHealth from an IT project into a continuous service improvement program (Betto et al., 2022; Kaplan & Norton, 1992).

6. CONCLUSION

6.1. Conclusion

This study presented a JASP-compatible panel data research manuscript on mobile health application adoption in Indonesian private hospitals. Using a synthetic balanced panel of hospital-quarter observations, the analysis demonstrates how mixed models can evaluate adoption drivers and service outcomes while accounting for repeated observations within hospitals. The findings suggest that system quality, information quality, privacy assurance, management support, staff training, marketing support, and SATUSEHAT integration are positively associated with mHealth active use. Active use is associated with higher patient satisfaction and shorter outpatient waiting times.

The most important message for hospital management is that adoption depends on the fit between technology, service processes, governance, and staff capabilities. Mobile health applications create value by making patient journeys easier, trustworthy, and operationally connected to hospital workflows. Private hospitals in Indonesia can use the attached CSV structure to build their own panel dataset, import it into JASP, and replace synthetic results with real evidence. For academic researchers, this paper offers an IMRAD and APA-style template that can be developed into a stronger empirical manuscript once real data, validated measures, and ethical approvals are available.

6.2. Limitations and Future Research

This study has several limitations must be acknowledged. First, the dataset was synthetic. It was generated to resemble plausible private hospital operational data but did not measure actual hospitals. Therefore, the coefficient estimates, p-values, and fitted values should not be used to make factual claims about the Indonesian hospital sector. Second, the adoption variables were aggregated at the hospital-quarter level. Aggregation is appropriate for management dashboards, but it hides variations between patient segments, clinical departments, age groups, insurance categories, and service lines. Third, the models are associative. Even in real data, higher active use could reflect better hospitals rather than a causal effect of the applications. Stronger causal designs are needed to estimate the impact of mHealth interventions.

Future research should collect real panel data from private hospitals, ideally from multiple hospital groups and provinces. Researchers should combine administrative data with patient surveys to validate active-use measures and understand the adoption barriers among different patient groups. Future work should also document the implementation history of each hospital, including vendor changes, application redesigns, pricing policies, and service line expansion, because these events can explain sudden shifts in adoption trajectories. A mixed-methods design could add interviews with hospital executives, IT managers, clinicians, and front-office staff to explain why some hospitals translate digital tools into better services while others do not. Finally, future studies should examine economic outcomes, such as cost per outpatient visit, revenue per patient, no-show rate, and retention. These outcomes would directly speak to business-management journals and private hospital strategies.

Ethical Approval

Not Applicable

Informed Consent Statement

Not Applicable

Authors' Contributions

Not Applicable

Disclosure Statement

No potential conflict of interest was reported by the author(s).

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The data presented in this study are available on request from the corresponding author due to privacy reasons.

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