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Knowledge Sharing Among Public Hospital Staff: An Extended UTAUT Study of Clinical Knowledge Exchange

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ABSTRACT
Clinical knowledge sharing in public hospitals is critical for patient safety, continuity of care, and service quality, yet it is often constrained by workload, fragmented information systems, and uncertainty about privacy and accountability. This manuscript develops an extended Unified Theory of Acceptance and Use of Technology (UTAUT) model to explain staff intention to use approved digital communication tools for clinical knowledge exchange and the resulting exchange behavior. Beyond core UTAUT constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions), the model incorporates task-technology fit, trust in digital communication, and perceived privacy and security risk. A quantitative cross-sectional design is proposed for public hospital settings using partial least squares structural equation modeling to test direct and indirect effects, with controls for profession, tenure, and technology experience. The study's main contribution is a context-specific hypothesis set and an implementable measurement item bank for administrators seeking to strengthen organizational learning and digital governance in hospitals.

Keywords
Knowledge sharing, Public Hospital, UTAUT, Task-Technology Fit, Trust.

Introduction

Public hospitals are frontline public service organizations tasked with delivering safe, equitable, and efficient care under strong accountability and, often, limited resources (Ismanto et al., 2024) . Because patient needs are complex and time-sensitive, service quality depends not only on physical infrastructure and clinical competence but also on how quickly staff can access and exchange reliable knowledge. Knowledge sharing, which is defined as the deliberate exchange of practical, experience-based, and evidence-based information among staff, is a core capability for service quality and organizational learning. Evidence from public hospital contexts indicates that knowledge-sharing practices differ across professional groups and are shaped by leadership routines, workload, and the availability of institutional mechanisms that promote collaboration and learning (Chitha et al., 2026; Kassa and Ning, 2023). However, improvements in knowledge exchange increasingly depend on digital communication and hospital information systems, which introduce new governance issues related to privacy, security, and traceability (Cordeiro et al., 2024; Merge et al., 2019).

Digital channels can strengthen handovers and reduce omissions of critical information, but adoption remains uneven and is frequently constrained by training burdens, inconsistent infrastructure, and weak integration with clinical workflows (Agha-Mir-Salim et al., 2025). Moreover, technology-enabled communication introduces governance risks. In this case, staff may worry about privacy, security, traceability, and accountability, especially when patient-related information is shared across devices or networks. Recent evidence shows that even when secure clinical communication tools exist, workflow design and usability problems can contribute to errors such as wrong-patient ordering, underlining that digital communication must be both safe and usable (Lou et al., 2024).

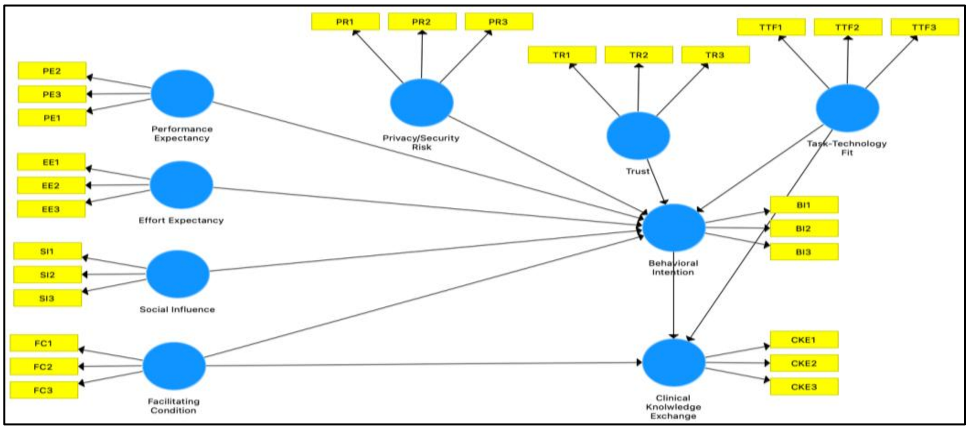
From the standpoint of public administration, this issue connects organizational learning and digital governance. Digital transformation in public organizations is not only the adoption of new tools but also a coordinated change in processes, capabilities, and accountability arrangements (Merge et al., 2019). In hospitals, this change interacts with professional autonomy, hierarchical decision-making, and the realities of shift work. As a result, a policy decision to deploy a platform does not automatically translate into consistent use for clinical knowledge exchange. Understanding what drives staff intention to use approved digital tools and how that intention translates into actual clinical knowledge exchange is essential for designing interventions that improve service reliability.

To explain and predict adoption and use of technology in organizations, the Unified Theory of Acceptance and Use of Technology (UTAUT) proposes that performance expectancy, effort expectancy, social influence, and facilitating conditions shape behavioral intention and use behavior (Venkatesh et al., 2003). UTAUT has been widely applied in health care, and meta-analytic evidence confirms that performance expectancy and behavioral intention are among the strongest determinants of health technology use (Thanthrige et al., 2025; Demsash et al., 2024). Nevertheless, hospital knowledge sharing presents additional requirements. Task-technology fit (TTF) argues that adoption and performance improve when technology features match task requirements (Chansanguan, 2025; Goodhue et al., 1995). This is particularly salient in hospitals, where communication tasks include time-critical handovers, multidisciplinary coordination, and context-rich interpretation of clinical cues. Thus, the use of technology in the knowledge-sharing process must fit clinical tasks, users must trust communication channels and data handling, and staff may perceive privacy and security risks when exchanging patient-related knowledge. Integrated UTAUT-task-technology fit evidence supports extending UTAUT with fit-related constructs in health care settings (Thanthrige et al., 2025; Chansanguan, 2025).

Since hospital communication tasks are diverse and time critical, task-technology fit emphasizes that performance benefits arise when system capabilities align with task requirements and working conditions (Goodhue et al., 1995). If staff perceive poor alignment, such as difficult access at bedside, slow workflows, or missing clinical fields, intention and sustained use decline even if training exists. Evidence suggests that digital applications can facilitate cross-provider knowledge sharing when they support relevance, integration, and boundary coordination, reinforcing fit as a key determinant (Aggestam et al., 2025).

Moreover, trust in a system reflects belief that it will operate reliably and predictably and support the user's goals (McKnight et al., 2002). In clinical exchange, trust is vital because staff must rely on timely message delivery and correct patient-context linkage. Conversely, privacy and security concerns can reduce willingness to share knowledge digitally, especially when staff fear unauthorized access or misuse of patient-related data (Alhammad et al., 2024; Malhotra et al., 2004). Digital knowledge exchange in public hospitals is therefore a governed practice shaped by both adoption drivers and compliance constraints.

Figure 1. Conceptual model of the extended UTAUT framework for clinical knowledge exchange.



Source: SmartPLS Modelling

Based on the arguments above, performance expectancy (H1), effort expectancy (H2), social influence (H3), facilitating conditions (H4), task-technology fit (H5), trust (H6), and perceived privacy/security risk (H7) are proposed as predictors of behavioral intention. Behavioral intention is expected to predict clinical knowledge exchange behavior (H8), while facilitating conditions and task-technology fit are expected to directly support behavior (H9–H10). The complete hypothesis table appears in Table 1.

Table 1. Hypotheses for the extended UTAUT model.

Hypothesis	Path	Direction	Rationale
H1	PE → BI	+	Higher perceived performance gains increase intention to use digital tools.
H2	EE → BI	+	Greater ease of use increases intention.
H3	SI → BI	+	Peer and supervisor expectations increase intention.
H4	FC → BI	+	Perceived organizational and technical support increases intention.
H5	TTF → BI	+	Better alignment between tool features and clinical tasks increases intention.
H6	TR → BI	+	Higher trust in the communication channel increases intention.
H7	PR → BI	-	Higher perceived privacy/security risk decreases intention.
H8	BI → CKE	+	Higher intention increases clinical knowledge exchange behavior.
H9	FC → CKE	+	Supportive conditions directly enable knowledge exchange behavior.
H10	TTF → CKE	+	Fit directly facilitates effective exchange in workflow.

Source: Proposed by researcher

Furthermore, the research develops an extended UTAUT framework tailored to clinical knowledge exchange in public hospitals and provides a complete hypothesis set and measurement item bank to support a quantitative study design. The proposed model is intended for research and for practical diagnosis by administrators who need evidence-based levers to strengthen knowledge sharing, reduce preventable communication failures, and improve service performance.

Method

A quantitative cross-sectional survey was proposed in 3 public hospitals in Southeast Sulawesi, where staff are required or encouraged to use approved digital channels for clinical communication and knowledge exchange. The unit of analysis was the individual staff member. The target population included physicians, nurses, pharmacists, allied health professionals, laboratory staff, radiographers, and unit administrators involved in clinical communication. The total sample of this research was 135, as recommended by Hair et al. (2019), where a minimum sample size was 5-10 times the number of indicators (manifest variables) of all latent variables in structural equation modeling (SEM). All constructs were measured using multi-item Likert indicators (1=strongly disagree to 5=strongly agree) adapted from validated scales. UTAUT items followed established operationalization (Venkatesh et al., 2003), task-technology fit draws from fit measures (Goodhue et al., 1995), trust items follow validated IS trust scales (McKnight et al., 2002), and privacy/security risk items are adapted from privacy concern literature (Alhammad et al., 2024; Malhotra et al., 2004). Clinical knowledge exchange items are adapted from knowledge-sharing behavior measures (Bock et al., 2005; Kankanhalli et al., 2005). The detail of Measurement item can be see in the Table 2.

Furthermore, for data analysis strategy, PLS-SEM is used for testing the extended UTAUT model, given its suitability for prediction-oriented models with multiple predictors (Hair et al., 2019). Measurement reliability and validity were assessed through composite reliability, AVE, and HTMT discriminant validity (Henseler et al., 2015). Structural model evaluation included path coefficients, effect sizes, and explained variance. Bootstrapping tested indirect effects and mediation via behavioral intention. Common method bias was minimized through procedural controls and checked using recommended remedies (Podsakoff et al., 2003).

Table 2. Measurement item bank

Construct (code)	Item code	Measurement item statements
Performance Expectancy (PE)	PE1	Using approved digital tools improves the quality of my clinical work.
Performance Expectancy (PE)	PE2	Using approved digital tools helps me share clinical information faster.
Performance Expectancy (PE)	PE3	Using approved digital tools reduces information gaps during handovers.
Effort Expectancy (EE)	EE1	Learning to use approved digital tools is easy for me.
Effort Expectancy (EE)	EE2	My interaction with approved digital tools is clear and understandable.
Effort Expectancy (EE)	EE3	It is easy for me to become skillful at using approved digital tools.
Social Influence (SI)	SI1	People who influence my work think that I should use approved digital tools.
Social Influence (SI)	SI2	Hospital leaders encourage the use of approved digital tools for knowledge exchange.
Social Influence (SI)	SI3	My colleagues value the use of approved digital tools for clinical communication.
Facilitating Conditions (FC)	FC1	I have the resources needed to use approved digital tools.
Facilitating Conditions (FC)	FC2	I have the knowledge needed to use approved digital tools.

Facilitating Conditions (FC)	FC3	A specific person or group is available for assistance when I have difficulties.
Task-Technology Fit (TTF)	TTF1	Approved digital tools provide features that match my clinical communication tasks.
Task-Technology Fit (TTF)	TTF2	Approved digital tools are well suited for time-critical handover communication.
Task-Technology Fit (TTF)	TTF3	Using approved digital tools fits the way my unit coordinates patient care.
Trust (TR)	TR1	I trust approved digital tools to reliably deliver my clinical messages.
Trust (TR)	TR2	I believe approved digital tools handle clinical information in a dependable way.
Trust (TR)	TR3	I feel confident relying on approved digital tools for clinical communication.
Privacy/Security Risk (PR)	PR1	I worry that clinical information shared digitally could be accessed by unauthorized people.
Privacy/Security Risk (PR)	PR2	I am concerned about privacy or security consequences of sharing clinical knowledge digitally.
Privacy/Security Risk (PR)	PR3	I think digital sharing increases the risk of misuse of patient-related information.
Behavioral Intention (BI)	BI1	I intend to use approved digital tools for clinical knowledge exchange in the next months.
Behavioral Intention (BI)	BI2	I will frequently use approved digital tools to share clinical updates.
Behavioral Intention (BI)	BI3	I plan to use approved digital tools whenever they are appropriate for my tasks.
Clinical Knowledge Exchange (CKE)	CKE1	I frequently share clinical tips, procedures, or best practices through approved channels.
Clinical Knowledge Exchange (CKE)	CKE2	I share patient-safety relevant updates with colleagues in a timely manner.
Clinical Knowledge Exchange (CKE)	CKE3	I exchange clinical knowledge across professions or units when needed.

Source: Venkatesh et al (2003), Goodhue et al (1995), McKnight et al (2002), Alhammad et al (2024), Malhotra et al (2004), Bock et al (2005), Kankanhalli et al (2005).

Result and Discussion

Result

1. Respondent profile and descriptive statistics

This study surveyed 135 clinical staff from three public hospitals in Southeast Sulawesi, where staff are required or encouraged to use approved digital channels for clinical communication and knowledge exchange. Respondents represented multiple clinical roles involved in day-to-day clinical communication. Table 3 presents the distribution of respondents by job background.

Table 3. Respondent profile by clinical job background

Clinical job background	**n**	**%**
nurses	45	33.3
pharmacists	36	26.7

unit administrators	19	14.1
laboratory staff	17	12.6
radiographers	12	8.9
physicians	6	4.4

Source: Survey data (n=135) (2025)

Descriptive statistics of the study constructs are shown in Table 4. Overall mean scores were relatively high (≈3.9–4.1), suggesting that respondents generally perceived approved digital tools as useful, supported, and integrated into routine communication. Perceived privacy/security risk also showed a high mean, indicating that privacy and accountability concerns remain salient even in 'approved' communication environments.

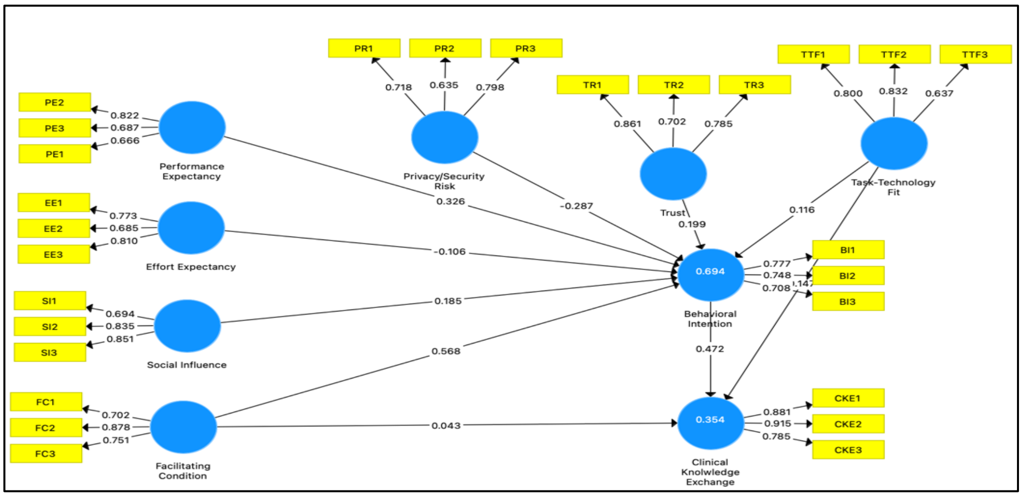
Table 4. Descriptive statistics of latent constructs

Construct	**Mean**	**SD**
PE	4.002	0.463
EE	4.000	0.525
SI	3.906	0.595
FC	4.104	0.519
TTF	4.027	0.523
TR	3.914	0.574
PR	4.086	0.517
BI	4.012	0.508
CKE	3.825	0.669

Source: Data Processed (2025)

2. Measurement model evaluation

The reflective measurement model was assessed for indicator reliability, internal consistency reliability, and convergent and discriminant validity. Indicator loadings were statistically significant and ranged from 0.635 to 0.915 (Table 5), indicating adequate indicator reliability for the majority of items. Items with loadings slightly below 0.70 were retained because construct-level reliability and AVE met recommended thresholds.



Source: PLS Algorithm Calculation (2025

Table 5. Outer loadings (reflective indicators)

Construct	Indicator	Loading	t	p
BI	BI1	0.777	12.630	0.000
BI	BI2	0.748	6.618	0.000
BI	BI3	0.708	13.973	0.000
CKE	CKE1	0.881	42.036	0.000
CKE	CKE2	0.915	34.225	0.000
CKE	CKE3	0.785	12.877	0.000
EE	EE1	0.773	6.810	0.000
EE	EE2	0.685	2.452	0.015
EE	EE3	0.810	6.069	0.000
FC	FC1	0.702	5.687	0.000
FC	FC2	0.878	37.502	0.000
FC	FC3	0.751	12.256	0.000
PE	PE2	0.822	13.833	0.000
PE	PE3	0.687	9.244	0.000
PR	PR1	0.718	5.807	0.000
PR	PR2	0.635	4.205	0.000
PR	PR3	0.798	7.938	0.000
SI	SI1	0.694	6.166	0.000
SI	SI2	0.835	14.812	0.000
SI	SI3	0.851	30.925	0.000
TR	TR1	0.861	24.290	0.000
TR	TR2	0.702	6.197	0.000
TR	TR3	0.785	11.106	0.000
TTF	TTF1	0.800	12.666	0.000
TTF	TTF2	0.832	6.867	0.000
TTF	TTF3	0.637	2.686	0.007
PE	PE1	0.666	5.105	0.000

Source: Data Processed (2025)

Internal consistency reliability was acceptable, with composite reliability (CR) values between 0.762 and 0.896 and Cronbach's alpha ranging from 0.534 to 0.828 (Table 6). Convergent validity was supported because all AVE values exceeded 0.50 (0.519–0.743).

Table 6. Reliability and convergent validity

Construct	Cronbach's α	CR	AVE	Loading range
PE	0.556	0.771	0.531	0.666–0.822
EE	0.637	0.801	0.574	0.685–0.810
SI	0.711	0.838	0.634	0.694–0.851
FC	0.679	0.823	0.610	0.702–0.878
TTF	0.635	0.803	0.579	0.637–0.832
TR	0.684	0.827	0.616	0.702–0.861
PR	0.534	0.762	0.519	0.635–0.798
BI	0.587	0.789	0.555	0.708–0.777
CKE	0.828	0.896	0.743	0.785–0.915

Source: Data Processed (2025)

Furthermore, discriminant validity was examined using the Fornell–Larcker criterion (Table 7). The criterion was satisfied for all construct pairs except facilitating conditions (FC) and perceived privacy/security risk (PR), where the inter-construct correlation (r=0.835) exceeded the square root of AVE for both constructs. This indicates potential conceptual overlap or context-specific coupling between organizational support and risk awareness in the studied hospitals; this issue is addressed as a limitation in the discussion. Collinearity diagnostics indicated no problematic multicollinearity in the structural model. Variance inflation factors (VIF) for predictors of behavioral intention ranged from 1.85 to 4.73, and VIFs for predictors of clinical knowledge exchange ranged from 1.42 to 2.27, which are below the conservative threshold of 5.00.

Table 7. Discriminant validity (Fornell–Larcker criterion)

	PE	**EE**	**SI**	**FC**	**TTF**	**TR**	**PR**	**BI**	**CKE**
PE	0.729	0.599	0.477	0.583	0.521	0.469	0.611	0.661	0.443
EE	0.599	0.758	0.462	0.578	0.673	0.612	0.597	0.532	0.334
SI	0.477	0.462	0.796	0.611	0.460	0.520	0.548	0.639	0.789
FC	0.583	0.578	0.611	0.781	0.457	0.437	0.835	0.711	0.446
TTF	0.521	0.673	0.460	0.457	0.761	0.738	0.611	0.531	0.417
TR	0.469	0.612	0.520	0.437	0.738	0.785	0.429	0.595	0.393
PR	0.611	0.597	0.548	0.835	0.611	0.429	0.720	0.581	0.461
BI	0.661	0.532	0.639	0.711	0.531	0.595	0.581	0.745	0.580
CKE	0.443	0.334	0.789	0.446	0.417	0.393	0.461	0.580	0.862

Source: Data Processed (2025)

3. Structural model evaluation and hypothesis testing

The structural model explained a substantial proportion of variance in behavioral intention (R^2=0.694) and a moderate proportion of variance in clinical knowledge exchange behavior (R^2=0.354). Table 8 summarizes the direct effects and hypothesis testing results based on bootstrapping.

Table 8. Structural paths and hypothesis testing results

Hyp.	**Path**	**Expected**	**β**	**t**	**p**	**95% CI**	**f²**	**Decision**
H1	PE -> BI	+	0.326	4.055	0.000	[0.150, 0.457]	0.182	Supported
H2	EE -> BI	+	-0.106	1.286	0.199	[-0.245, 0.074]	0.015	Not supported
H3	SI -> BI	+	0.185	2.671	0.008	[0.062, 0.333]	0.061	Supported
H4	FC -> BI	+	0.568	5.140	0.000	[0.328, 0.779]	0.246	Supported
H5	TTF -> BI	+	0.116	1.263	0.207	[-0.083, 0.287]	0.013	Not supported
H6	TR -> BI	+	0.199	2.182	0.030	[-0.001, 0.370]	0.048	Supported
H7	PR -> BI	-	-0.287	2.661	0.008	[-0.465, -0.047]	0.057	Supported
H8	BI -> CKE	+	0.472	4.378	0.000	[0.239, 0.665]	0.152	Supported
H9	FC -> CKE	+	0.043	0.360	0.719	[-0.194, 0.282]	0.001	Not supported
H10	TTF -> CKE	+	0.147	1.650	0.100	[-0.038, 0.320]	0.023	Not supported

Source: Data Processed (2025)

Facilitating conditions (β=0.568, p<0.001) and performance expectancy (β=0.326, p<0.001) were the strongest positive predictors of behavioral intention to use approved digital channels for clinical communication. Social influence (β=0.185, p=0.008) and trust (β=0.199, p=0.030) also increased intention, whereas perceived privacy/security risk significantly reduced intention (β=-0.287, p=0.008). Effort expectancy and task–technology fit were not significant predictors of intention in this context. For behavioral outcomes, behavioral intention significantly predicted clinical knowledge exchange (β=0.472, p<0.001), but the direct effects of facilitating conditions and task–technology fit on behavior were not statistically significant at α=0.05.

4. Indirect effects and mediation via behavioral intention

Bootstrapping was used to examine indirect effects of the antecedents on clinical knowledge exchange through behavioral intention. As shown in Table 9, several antecedents exhibited significant mediated effects, supporting behavioral intention as a key mechanism linking technology acceptance and knowledge exchange behavior.

Table 9. Indirect effects on clinical knowledge exchange via behavioral intention

Indirect path (via BI)	**β**	**t**	**p**	**95% CI**	**Interpretation**
FC -> BI -> CKE	0.268	3.824	0.000	[0.121, 0.396]	Significant
PE -> BI -> CKE	0.154	3.054	0.002	[0.057, 0.247]	Significant
PR -> BI -> CKE	-0.136	2.356	0.019	[-0.235, -0.020]	Significant
TR -> BI -> CKE	0.094	1.986	0.048	[-0.000, 0.193]	Significant
SI -> BI -> CKE	0.087	1.845	0.066	[0.018, 0.195]	Marginal
TTF -> BI -> CKE	0.055	1.144	0.253	[-0.039, 0.156]	Not significant
EE -> BI -> CKE	-0.050	1.224	0.222	[-0.124, 0.037]	Not significant

Source: Data Processed (2025)

The indirect effect of facilitating conditions on clinical knowledge exchange through behavioral intention was large and significant (β=0.268, p<0.001), while its direct effect on behavior was not significant, indicating full mediation in this sample. Performance expectancy (β=0.154, p=0.002) and trust (β=0.094, p=0.048) also influenced behavior indirectly via intention. Conversely, perceived privacy/security risk had a significant negative indirect effect (β=-0.136, p=0.019), implying that risk concerns reduce clinical knowledge exchange primarily by lowering willingness to use the approved digital channels.

Discussion

A central theme emerging from the data is the critical role of community participation in shaping tourism village development. Local residents in Toronipa actively participate in planning, managing, and maintaining tourism facilities through community-based institutions and informal networks. This participatory governance structure strengthens a sense of ownership and social legitimacy, which has been identified as a key determinant of sustainable tourism village development (Latif, 2018; Pamuja et al., 2025).

This study provides evidence that, in public hospital settings where staff are required or strongly encouraged to use approved digital communication channels, organizational enabling conditions become the dominant lever for strengthening digital clinical knowledge sharing. Based on the SEM model calculation, Facilitating Conditions (FC) showed the largest effect on Behavioral Intention and also produced a strong mediated effect on Clinical Knowledge Exchange (CKE) through BI. This pattern is highly consistent with the core logic of UTAUT, where FC represents the organizational and technical readiness that enables sustained system use, especially when adoption is intertwined with institutional routines and compliance expectations (Venkatesh et al., 2003).

It also fits well with public-sector digital transformation arguments that capability, infrastructure, and governance shape whether digital reforms become routine practice rather than short-lived initiatives (Mergel et al., 2019). Furthermore, the result also consistent with qualitative evidence syntheses on digital hospitals showing staff experience and sustained use depend heavily on implementation supports, service reliability, training, and workflow enablement (Canfell et al., 2024). It also resonates with broader public-sector KM evidence that organizational mechanisms and institutional arrangements shape knowledge practices (Kassa & Ning, 2023).

Performance expectancy (PE) significantly predicts intention also shows a significant mediated effect on behavior. In clinical environments, usefulness factor is experienced as speed gaps. This aligns with healthcare adoption syntheses where PE and BI are repeatedly among the strongest determinants (Thanthrige et al., 2025; Demsash et al., 2024). Moreover, social influence (SI) has a positive effect on intention. In public institutions, compliance and hierarchy can amplify SI: endorsement from leadership, head nurses, and senior physicians can “normalize” channel use and discourage off-platform workarounds. This is consistent with study that shows adoption consolidates when leadership and peer norms legitimize the new routine (Demsash et al., 2024).

The results show trust (TR) increases intention and trust also has a significant indirect link to exchange behavior. Meanwhile, perceived privacy/security risk (PR) reduces intention and indirectly reduces clinical knowledge exchange. A system-level scoping review emphasizes sociotechnical needs such as reliability, usability, workflow embedding has important for handover communication (Agha-Mir-Salim et al., 2025). Empirical secure-messaging research also highlights safety and cognitive risks such as perceptions of secure clinical communication are tied to errors like wrong-patient ordering (Lou et al., 2024). It also worth noting that high secure-messaging use can associate with increased workload and attention switching, suggesting governance and workflow design must be managed together (Lew et al., 2025). Broader eHealth acceptance research that integrates trust–risk mechanisms also reports the same directional logic. Higher trust supports intention while perceived risk undermines it. (Arfi et al., 2021).

However, Effort expectancy (EE) is not significant for intention. This often happens when baseline usability is already "good enough," so ease-of-use no longer differentiates intention once FC, PE, trust, and risk are considered. The non-significant result also may appear when staff comply regardless of ease because policy/expectations dominate or effort effects are absorbed into FC (training/support) or confounded by workload pressures. Evidence from secure messaging shows that even usable tools can increase cognitive burden through interruptions/attention switching (Lew et al., 2025).

TTF does not significantly predict intention and its direct effect on behavior is marginal. It may happen when staff use approved channels because they are expected to, even if the tool is not perfectly aligned with clinical workflows. However, the total effect value of TTF on clinical knowledge exchange is positive which indicates that TTF contributes to behavior when combined with other pathways.This aligns with healthcare knowledge exchange view that applications facilitate cross-provider sharing when they support coordination boundaries and integration (Aggestam et al., 2025). It also aligns with secure messaging network studies showing role-based connectivity and usage behaviors vary, implying fit differs by profession and setting (Baratta et al., 2022).

Finally, the structural model explains substantial variance in behavioral intention (R^2=0.694) and moderate variance in clinical knowledge exchange (R^2=0.354). The mediated effects where FC, PE, TR, and PR influence CKE through BI show that the most practical way to increase knowledge exchange is to raise consistent intention through strong enabling conditions and governance confidence.

Conclusion

This study examined the determinants of clinical knowledge exchange (CKE) through approved digital communication channels in three public hospitals in Southeast Sulawesi using an extended UTAUT model. The findings showed that the model explained a large proportion of variance in behavioral intention to use approved channels and a meaningful proportion of variance in CKE behavior.

The results confirmed that organizational enabling conditions were the most influential lever for strengthening digital knowledge sharing in public hospitals. Facilitating conditions had the strongest positive effect on intention, and its contribution to CKE operates mainly through behavioral intention (strong mediation). Beyond organizational support, performance expectancy and social influence significantly increased intention, indicating that clinicians are more willing to use approved tools when they perceive clear performance benefits and when usage was reinforced through leadership encouragement and peer norms.

Crucially, the study demonstrated that digital knowledge sharing in hospitals was not only an adoption issue but also a governance issue. Trust in the approved channel strengthened intention, while privacy/security risk reduced intention and indirectly reduced clinical knowledge exchange. These findings implied that even in "approved" systems, clinicians remain sensitive to confidentiality, traceability, and the consequences of misdirected or inappropriate messages. In contrast, effort expectancy and task–technology fit did not emerge as primary determinants of intention in this setting, suggesting that where channel use is already encouraged or expected, usability and feature fit become less decisive than support readiness and perceived governance safety.

Overall, the study highlights that improving clinical knowledge exchange via digital channels in public hospitals required more than deploying technology. The most effective strategy is to strengthen institutional readiness (facilitating conditions), demonstrate clear clinical performance value, reinforce leadership/peer norms, and implement risk-reduction and trust-building governance practices so that clinicians feel confident using approved channels consistently for clinical coordination and knowledge sharing.

Furthermore, there are some limitations to the research. First, this study used a one-time survey, so the relationships identified should be interpreted as associations, not causal effects. Changes in policy, infrastructure, or hospital leadership over time could alter intention and clinical knowledge exchange behaviors. Secondly, clinical knowledge exchange and channel use were captured through self-reported questionnaire items, which may be influenced by recall error and social desirability, especially because the use of approved channels is required/encouraged in these hospitals. This can inflate consistency across constructs. Third, because predictors and outcomes were collected from the same instrument and at the same time, common method variance may remain possible. In addition, the measurement results indicated close empirical proximity between facilitating conditions and perceived privacy/security risk, suggesting that respondents may perceive institutional support and governance/risk awareness as intertwined in these settings. Fourth, although data were collected from three public hospitals, findings reflect the governance, infrastructure, and organizational culture of public hospitals in Southeast Sulawesi. Transferability to private hospitals or other regions should be made cautiously.

Based on the research limitation, it is recommended for future research to adopt include additional predictors closer to real clinical behavior, such as workload/time pressure, psychological safety, interprofessional collaboration climate, knowledge-sharing norms, leadership style, and patient-safety culture. It is reasonable since the model explains intention strongly but behavior moderately (R^2 for CKE is lower than BI). The future research also can consider to replicate the reseach topic across other provinces with private hospitals and different hospital classes (type B/C/D). The broaden setting would strengthen external validity and enable analysis of how digital governance maturity moderates adoption and knowledge exchange.

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