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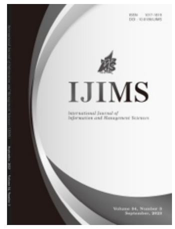

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Evaluating the Impact of SaaS-Based Electronic Health Record and Privacy Concern on Stakeholders' Benefits

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Keywords

Resource-Matching Theory (RMT), Stakeholder theory, Cloud computing, Privacy concern, Electronic Health Records (EHRs)

Abstract

The implementation of electronic health records (EHRs) combined with information communication technology (ICT) has become a trend in the medical industry. Therefore, the most important issue addressed in the study is whether Software-as-a-Service (SaaS) cloud computing technology supports EHRs management. This study was adopted Resource-matching theory (RMT) to examine the match between EHRs and SaaS; Stakeholder theory was adopted to discuss the benefits of using cloud-based EHRs. In addition, information privacy concern was a moderator between the matching of EHRs and SaaS. There were 356 valid respondents of medical personnel, and the hypotheses were tested using structural equation modeling. The results indicated that EHRs and SaaS were well-matched, cloud-based EHRs can benefit users, and partially supported the moderating effect of information privacy concern. It suggested that medical institutions should implement EHRs to manage medical records, and people can benefit from cloud-based EHRs to improve quality of care.

1. Introduction

The medical industry must adopt more effective management models to meet rising demands for quality of care (Holroyd-Leduc et al., 2011; Kuo, 2011). The Medical Records Institute (MRI) identified five phases of medical records: AMRs, CMRs, EMRs, EPRs, and EHRs. Electronic health records (EHRs) as the final stage, fully electronic and capable of delivering higher care quality (Menachemi & Collum, 2011; Guo et al., 2017). Taiwan's comprehensive medical environment, supported by National Health Insurance (NHI), faces growing care demands driven by health awareness, requiring effective management to sustain competitiveness (Chang et al., 2017). Yet, challenges include big data storage (Boonstra & Broekhuis, 2010; Fox, 2011). About 89% of Taiwan's hospitals have computerized patient records, though only 59.8% of clinics have partial EMRs, with few reaching full EHR development (Chang et al., 2017; Hwang & Lin, 2020). High costs and low ROI remain barriers (Chang et

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al., 2017; Schweitzer, 2012). Importantly, cloud computing through Software-as-a-Service (SaaS), the most visible layer to end users, enhances EHR applications, making them more comprehensive and convenient for medical personnel and patients (Stanoevska-Slabeva & Wozniak, 2010; Marston et al., 2011; Sultan, 2014).

Drawn upon the above discussion, it leads to a need to understand: *Can SaaS and EHRs be matched? Will it present effective performance to benefit the patients, medical personnel, and the hospital?* According to resource-matching theory (Anand & Sternthal, 1989), resources are considered matched when the available cognitive resources align with those required. In hospitals, EHRs represent a critical resource, and cloud-based EHRs are expected to be supported by cloud computing (SaaS) as the matching resource, thereby maximizing benefits for stakeholders such as patients, medical personnel, and hospitals (Brower & Mahajan, 2013; Demirkan & Delen, 2013). However, Cilliers (2020) noted that healthcare wearable users often lack awareness of information security risks, highlighting the importance of privacy concerns. Thus, this study proposes that privacy concern moderates the relationship between SaaS and EHR matching. While prior studies examined the interaction of decision aid features and attribute load (Mitsuhashi & Greve, 2009; Tan et al., 2010), few have addressed the resource–feature matching effect in healthcare technology. To address this gap, this study develops a research model based on RMT to explore the matching between SaaS features and EHR characteristics, and applies stakeholder theory to examine hospital, patient, and medical personnel benefits. Furthermore, privacy concern is included as a moderator in the SaaS–EHR matching process. Accordingly, the main objectives of this study are:

(1) To ensure the Software-as-a-Service features, EHRs characteristics, and categories and benefits of hospital stakeholders to develop the conceptual model.

(2) To examine the characteristics matching between SaaS and EHRs, and the effect of cloud-based EHRs on stakeholder benefits (hospital benefits, and patient & medical personnel benefits).

(3) To examine the moderating effect of privacy concern in the relationship between SaaS/EHRs, and the matching.

2. Literature Review and Hypotheses Development

2.1. Cloud Computing and Service Features

With the rapid development of information technology and cloud computing, mobile cloud healthcare systems show great potential in individualized preventive healthcare (Wang et al., 2019; Zhang et al., 2010; Nikkhah et al., 2021). Cloud computing has been defined in various contexts (Stanoevska-Slabeva & Wozniak, 2010; Marston et al., 2011; Li, 2011). The National Institute of Standards and Technology (NIST) defines it as a model enabling ubiquitous, on-demand access to shared computing resources with minimal management or provider interaction (Mell & Grance, 2011; Schweitzer, 2012). NIST classifies cloud types into public, private, community, and hybrid, and its architecture into three layers: Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS), and Software-as-a-Service (SaaS). For end-users, SaaS is the most visible layer, providing easily accessible applications (Stanoevska-Slabeva & Wozniak, 2010; Zhang et al., 2010; Li, 2011; Asan et al., 2018). According to Lee et al. (2009), key features of

SaaS include:

(1) **Reusability**, SaaS software is delivered over the Internet and typically follows a one-to-many model (Lee et al., 2009). In this study, reusability refers to the ability of software and Internet resources to serve many users across different devices.

(2) **Data managed by provider**, SaaS is owned, delivered, and managed remotely by providers (Armbrust et al., 2010), who are responsible for data management and protection in their servers or data centers (Lee et al., 2009).

(3) **Service customizability**, this refers to services that can be modified by consumers to meet different needs (Lee et al., 2009). SaaS providers can deliver on-demand services to end-users without limitation.

(4) **Availability**, SaaS services are accessible via web browsers over the Internet regardless of time and location (Lee et al., 2009). Without Internet connection, SaaS becomes unusable, as cloud services are essentially web-based (Armbrust et al., 2010).

(5) **Scalability**, scalability refers to the ability to handle growing workloads or be expanded easily (Lee et al., 2009). SaaS offers elastic scalability, a distinct advantage of cloud computing (Gao et al., 2011).

(6) **Pay per use**, SaaS follows a rental model where users pay on demand for computing power and storage (Chang et al., 2017). Terms such as "pay for what you use" and "pay-as-you-go" are widely used to describe this feature (Demirkan & Delen, 2013; Marston et al., 2011).

2.2. Electronic Health Records (EHRs) Characteristics

ISO-2005 defined EHR as "*a repository of information regarding the health status of a subject of care in computer process able form, stored and exchanged securely, and accessible by multiple authorized users. It contains retrospective, concurrent, and prospective information and its primary purpose is to support continuing, efficient and quality integrated healthcare"* (Hayrinen et al., 2008). EHR is not only used by health care professionals such as physicians, nurses, but also by administrative staff (Garde et al., 2007; Chang et al., 2017; Hayrinen et al., 2008; Hoerbst & Ammenwerth, 2010). Rahimi et al. (2009) concluded that health information in the EHR will be right information for making correct healthcare decision. Following the definition of ISO-2005, a comprehensive characteristic of EHRs must include:

(1) **Interoperability**, refers to the ability of a system to interact with other systems (Hoerbst & Ammenwerth, 2010). EHRs should be compatible with multiple devices, including mobile, patient monitoring, PDAs, and other wireless devices (Resch & Tena, 2013; Chang et al., 2017).

(2) **Longitudinal**, EHRs should provide a lifelong record of care from birth to death (Garde et al., 2007; Latha et al., 2012), capturing retrospective, concurrent, and prospective medical data (Chang et al., 2017).

(3) **Granularity**, Demographic and clinical data support public health, population health, and patient care (Hayrinen et al., 2008; Latha et al., 2012).

(4) **Standardized logical information model**, data formats must follow standardized structures to enable cross-organizational sharing and individual health data management (Hoerbst & Ammenwerth, 2010; Hayrinen et al., 2008).

(5) **Persistence of information**, authorized users can store, modify, or delete data, while maintaining version control and amendment audit trails (ISO, 2005).

(6) **Completeness of information**, an ideal EHR should be comprehensive, integrating any type of health data from multiple providers (ISO, 2005). Comprehensive records allow physicians to view full patient histories and make accurate diagnostic decisions (Latha et al., 2012).

2.3. SaaS-EHR Characteristics Matching

Anand and Sternthal (1989) argued that resource-matching enables efficient processing when available and required cognitive resources align. The concept also explains successful alliances, where complementarity and compatibility facilitate partnerships (Mitsuhashi & Greve, 2009; Giboney et al., 2015). For health institutes, EHRs are the demanded resource, while SaaS provides the available IT resource to enhance user experience. Tan et al. (2010) showed that aids improving screening and alternative evaluation raise decision quality by reducing effort. Likewise, when SaaS features align with EHR characteristics, EHRs consolidate patient information and increase stakeholder benefits through improved services.

2.4. Stakeholder Benefits: Hospital and Personnel

Stakeholders are individuals or groups that influence or are influenced by firm activities (Shafiq et al., 2014; Chang et al., 2021). In EHRs, stakeholders include patients, physicians, payers, private industry, government, and entrepreneurs (Pagliari et al., 2012; Hwang & Lin, 2020). Kohli and Tan (2016) divided them into primary stakeholders, who generate and directly access patient care data, and secondary stakeholders, who have only indirect access, such as insurers and public health agencies.

Cloud-based EHRs are expected to increase stakeholder benefits by improving patient services, supporting medical personnel in decision-making, and reducing hospital costs (Chang et al. 2017). Following Kohli and Tan (2016), this study focuses on primary stakeholders, patients and providers, and defines benefits as individual (patients, medical personnel) and organizational (hospitals).

2.5 Moderating: Privacy Concern

Wang et al. (2016) indicated that individuals are concerned about the inappropriate collection, storage, profiling, and use of their personal information for unintended purposes without their consent. Privacy concern affects adoption intention of healthcare wearable devices in the healthcare (Rodrigues et al., 2013; Li et al., 2016). Cloud computing services make an user in an Internet-accessible environment can quickly share and interact with service providers (Yang & Lin, 2015; Nikkhah et al., 2021). Therefore, security issue is the biggest barrier and essential for a healthcare provider who plans to deploy a cloud-based EHRs (Rodrigues et al., 2013; Gu et al., 2017). Prior study reported that more than 86% of the respondents were worried about the private security problem, and 52% of the respondents suspected the reliability and availability of using cloud storage (Yang & Lin, 2015). Referring to the definition of Angst and Agarwal (2009), privacy concern is defined as the extent to which individuals are disturbed about the information collection practices of others. The measures content including collection, errors, unauthorized access, and secondary use.

3. Conceptual Framework and Hypotheses Development

Figure 1 demonstrates the conceptual framework of the study. The framework proposes that SaaS features can be well-matched with the EHR characteristics (SaaS-EHR matching), once the matching occurs, the cloud-based EHRs is expected to increase the stakeholder benefits. The SaaS features consist of reusability, data managed by provider, service customizability, availability, scalability, and pay per use; the EHR characteristics include interoperability, longitudinal, granularity, standardized logical information model, persistence of information, and completeness of information. Privacy concern is proposed to have moderating effect on the relationship between the matching of both SaaS and EHRs.

SaaS Features and EHR Characteristics vs. SaaS-EHR Characteristics Matching

The NIST suggested that industries adopt cloud computing for cost savings and IT agility (Schweitzer, 2012). Cloud computing enables EHRs to improve health care services, reduce startup expenses, support research, and facilitate data sharing (Chang et al., 2017). It also realizes data integration and interoperation for pervasive health monitoring (Chang et al., 2017; Chen et al., 2016; Gao et al., 2011). Furthermore, cloud infrastructure ensures authorization, confidentiality, and data integrity, allowing secure access to health records (Xu et al., 2017). In conclusion, cloud technology enhances EHR stability, accessibility, and accuracy. Accordingly, the following hypotheses are proposed:

H1: SaaS features (reusability, data managed by provider, service customizability, availability, scalability, and pay per use) are positively related to SaaS-EHR characteristics matching.

H2: EHR characteristics (interoperability, longitudinal, granularity, standardized logical information model, persistence of information, and completeness of information) are positively related to SaaS-EHR characteristics matching.

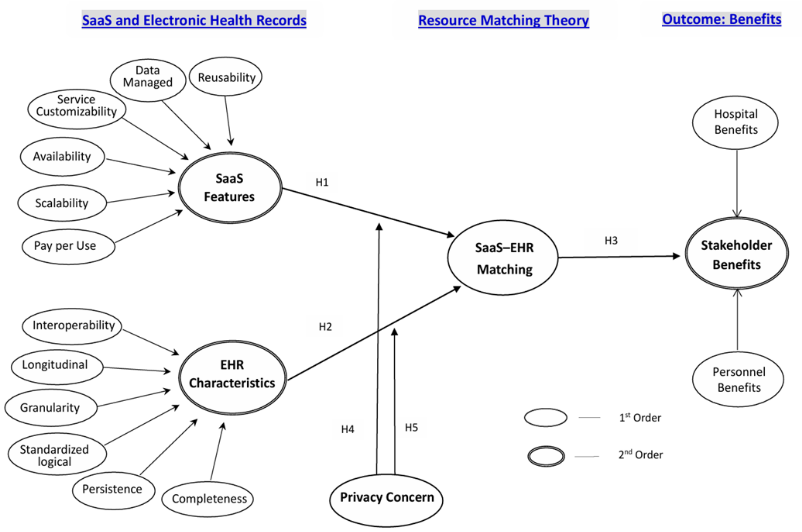

Fig. 1 *The Conceptual Framework*

SaaS-EHR Characteristics Matching vs. Stakeholder Benefits

Kohli and Tan (2016) indicated that EHRs should support primary stakeholders by improving patient care outcomes, expanding healthcare coverage, and reducing costs. A good match between SaaS features and EHR characteristics leads to outcomes such as improved care quality, reduced medical errors, efficient information sharing, physician time savings, and overall enhancements in care appropriateness (Menachemi & Collum, 2011). This study considers benefits for both hospitals and patients and medical personnel.

Hospital focus on whether cloud-based EHRs can increase revenues and reduce operational costs (Sultan, 2014; Xu et al., 2017). Organizational stakeholders (hospital) also improve patient flow by reminding patients and clinicians about subsequent visits (Chang et al., 2021; Menachemi & Collum, 2011; Mildon & Cohen, 2001), while enabling rapid medical resource sharing via cloud servers and the Internet (Chen et al., 2016; Menachemi & Collum, 2011). Moreover, EHR data significantly enhance prediction accuracy and decision-making (Xu et al., 2017; Virapongse et al., 2008; Rahman & Reddy, 2015).

Patients and Medical Personnel, quality of care and safety are paramount (Hung et al., 2013; Cilliers, 2020). Effective coordination improves service value and outcomes (Hung et al., 2013; Rahman & Reddy, 2015). Cloud-based EHRs address safety issues by leveraging data stored on servers (Russo et al., 2016; Singh & Sitting, 2016). With growing data capabilities, EHRs assist medical personnel in managing care, enhancing patient experiences, detecting safety risks, and raising provider awareness of potential threats (Russo et al., 2016; Singh & Sitting, 2016; Ford et al., 2016). Accordingly, the following hypotheses are proposed:

H3: SaaS-EHR characteristics matching is positively related to stakeholder benefits: (a) hospital benefits, and (b) patient and medical personnel benefits.

Moderating: Privacy Concern

Yang and Lin (2015) suggested that perceived risk of information disclosure deters technology adoption. Goode (2019) highlighted operational risks for cloud providers, while privacy and confidentiality remain crucial for EHR migration due to sensitive patient data (Rodrigues et al., 2013). Li et al. (2016) found that 82% of healthcare wearable users worry about privacy invasion. As cloud resources are provider-managed (Chen et al., 2016), weak privacy protection may cause mismatches between SaaS and EHRs, especially concerning health information (Asan et al., 2018). Accordingly, the following hypotheses are proposed:

H4: Privacy concern (collection, errors, unauthorized access, and secondary use) has a negative moderating effect on the relationship between SaaS features and SaaS-EHR characteristics matching.

H5: Privacy concern has a negative moderating effect on the relationship between EHR characteristics and SaaS-EHR characteristics matching.

4. Research Methodology, Data Analyses and Results

4.1. Research Design

There were totally five construct variables in the research model, which including three formative and The research model included five constructs: three formative and two reflective. The formative constructs were: SaaS features (reusability, data managed by provider, service customizability, availability, scalability, pay-per-use), EHR characteristics (interoperability, longitudinal, granularity, standardized logical information model, persistence of information, completeness of information), and stakeholder benefits (patient and medical personnel benefits, hospital benefits). The reflective constructs were SaaS–EHR matching and privacy concern (collection, errors, unauthorized access, and secondary use).

All measurement items were assessed on a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree). To ensure respondents understood cloud computing services, the questionnaire included five situational items referencing daily applications (e.g., Facebook, Gmail) and their usage patterns. A filter question was also added: "Do you know some cloud computing services require charges?" Respondents answering "I don't know" were excluded, as they might not reliably respond to items on pay-per-use.

4.2. Survey Administration

A pilot test verified scale reliability and internal consistency. Respondents were medical staff familiar with electronic patient records (e.g., doctors, personnel, administrators, IT staff). Totally 33 valid questionnaires were collected; item-to-total correlations exceeded .30 and Cronbach's alphas .70, except for seven SaaS feature items, which were revised based on literature and expert review. A second pilot with 35 responses showed item-to-total correlations of .395–.839; three items (EG1, ES1, CM5) were removed. Cronbach's alphas ranged from .736 to .870, confirming good reliability.

The formal survey used online (Facebook, BBS) and paper (mailed to institutes) methods. Respondents were medical staff with basic EHR knowledge. A total of 435 questionnaires were collected (290 online, 145 paper); after excluding 79 invalid, 356 valid samples remained (online=253, offline=103). Independent-sample t-tests found no significant online–offline differences in SaaS–EHR matching (F=0.216, t=0.699, p=.485) or stakeholder benefits (F=3.269, t=0.700, p=.484). Table 1 shows most respondents were from public/foundational hospitals in northern Taiwan, mainly medical centers or regional hospitals. Over half were medical personnel (56.5%), predominantly female (75.8%), mostly aged 21–30 (59.3%), and 50.9% had over three years' experience.

Table 1. *Demographic Characteristics* (n=356)

Category		Frequency	(%)	Category		Frequency	(%)
Gender	Male	86	24.2	Age	21~25	117	32.9
	Female	270	75.8		26~30	94	26.4
Education	High school	10	2.8		31~35	67	18.8
	College	67	18.8		36~40	37	10.4
	Bachelor	240	67.4		41~45	19	5.3
	Master	39	11.0		45 or above	22	6.1
Level of hospital	Medical center	110	30.9	Type of institution	Public hospital	137	38.5
	Regional hospital	142	39.9		Private hospital	46	12.9
	Regional teaching hospital	53	14.9		Foundational hospital	120	33.7
	Others	9	2.5		Clinic	38	10.7
Identification	Doctor	19	5.3		Others	15	4.2
	Medical personnel	201	56.5	Division	Medicine	77	21.6
	Administrative staff	61	17.1		Surgery	32	9.0
	Information Profess.	28	7.9		Ophthalmology	14	3.9
	Others	47	13.2		Orthopedics	18	5.0
Working experience	Less than 1 year	82	23.0		Dental	13	3.7
	1~3 years	93	26.1		Urology	16	4.5
	3~6 years	50	14.1		Rehabilitation	17	4.8
	6~10 years	46	12.9		Dermatology	17	4.8
	More than 10 years	85	23.9		Psychiatric	19	5.3
Location of institution	North	219	61.5		Obstetrics & Gynecology	23	6.5
	Middle	30	8.4		Pediatrics	28	7.9
	South	52	14.6		ENT, Family Medicine	35	9.8
	East	55	15.4		Others	47	13.2

4.3. Measurement Model Analysis

Table 2 demonstrated the EFA results. The results indicated that the overall KMO statistic was .929 (>.50), and Bartlett's Test of Sphericity was χ^2= 6110.902, and d/f= 210 (p<.001), which indicated sufficient sample size and large correlations between items for principal component analysis. SEM was conducted using PLS to assess measurement validity. Table 3 shows the CFA results: all standardized loadings exceeded .50 with t-values >1.96, and item-to-total correlations were above .50, indicating good internal consistency. All alphas, CRs, and AVEs surpassed recommended thresholds. Table 4 further confirmed discriminant validity, as the square roots of AVEs (diagonal values) were greater than inter-construct correlations. For the formative constructs (SaaS features, EHR characteristics, stakeholder benefits), all item weights were significant at the 95% confidence level (t>1.96), and VIFs were below 3.33 (Cenfetelli & Bassellier, 2009), indicating no multicollinearity. Common method bias (CMB) was also assessed. The largest single factor explained only 25.8% of variance, and the highest inter-construct correlation (r= .669, CD↔CR) was well below the .90 threshold. Thus, CMV was not a major concern in this study.

Table 2. *EFA Results of Stakeholder Benefits (n=356)*

Factors Stakeholder Benefits	Patient & Medical Personnel (SP)	Hospital Cost Efficiency (SH-c)	Hospital Work Efficiency (SH-w)
SP1	.761	.143	.260
SP2	.802	.126	.244
SP3	.732	.092	.172
SP4	.784	.118	.163
SP5	.804	.086	.298
SP6	.680	.136	.110
SP7	.756	.225	.274
SP8	.779	.327	.174
SP9	.768	.385	.125
SP10	.771	.389	.089
SH6	.148	.824	.283
SH7	.247	.824	.207
SH8	.238	.833	.202
SH9	.184	.844	.215
SH10	.179	.813	.246
SH1	.179	.178	.737
SH2	.036	.118	.738
SH11	.307	.224	.712
SH12	.399	.301	.630
SH13	.295	.348	.703
SH14	.379	.388	.610
Eigenvalue	10.412	2.587	1.535
Proportion	49.581	12.320	7.310
Cumulative	49.581	61.901	69.210
Cronbach's Alpha	.943	.932	.876
KMO and Bartlett Test	Kaiser-Meyer-Olkin		.929
	Bartlett	χ^2	6110.902***
		d/f	210

4.4. Structural Model Analysis

The PLS results in Figure 2 show that SaaS–EHR matching (R^2=25.8%) and stakeholder benefits (R^2=28%) were well explained. SaaS features (β=.285, t=3.083) and EHR characteristics (β=.339, t=4.772) had significant positive effects on SaaS–EHR matching, supporting H1 and H2. SaaS–EHR matching also positively affected stakeholder benefits (β=.529, t=8.075), supporting H3a and H3b. Table 5 and 6 summarizes the main effects. For moderation, a PLS competing model with K-means clustering divided respondents into low-PC (n=137, M=4.889) and high-PC (n=219, M=6.163) groups (F=735.632, $p<.001$). SaaS features had a weaker effect on SaaS–EHR matching for the high-PC group (β=.171, $p<.01$) than the low-PC group (β=.382, $p<.001$), supporting H4. However, the effect of EHR characteristics did not differ significantly between groups, so H5 was not supported.

Table 3 *Results of measurement model- CFA (n=356)*

Construct	Code	CR	CD	CC	CA	CS	CP	EI	EL	EG	ES	EP	EC	CM	SP	SH-c	SH-w	PC	PE	PU	PS	ITO	t-value
SaaS Features																							
Reusability	CR1	**.858**	.545	.463	.523	.362	.330	.210	.266	.195	.135	.254	.148	.297	.174	.256	.098	.021	.173	.195	.158	.738	21.133
	CR2	**.843**	.548	.373	.544	.384	.286	.212	.223	.224	.186	.264	.110	.243	.207	.235	.092	-.011	.181	.231	.205	.719	14.069
	CR3	**.851**	.590	.485	.571	.426	.228	.263	.258	.239	.172	.281	.166	.271	.203	.268	.108	.067	.197	.284	.254	.720	21.412
	CR4	**.853**	.596	.387	.583	.300	.283	.200	.258	.191	.140	.289	.112	.254	.190	.260	.041	-.008	.186	.332	.236	.734	16.713
Data Managed by Provider	CD1	.617	**.783**	.391	.429	.311	.312	.165	.210	.153	.134	.194	.129	.235	.153	.206	.092	.050	.146	.156	.166	.509	12.897
	CD2	.484	**.859**	.342	.350	.356	.177	.186	.221	.181	.059	.250	.122	.203	.186	.163	.127	.086	.134	.208	.212	.680	23.460
	CD3	.537	**.819**	.410	.492	.350	.199	.234	.291	.235	.155	.278	.144	.183	.172	.164	.079	.024	.121	.247	.159	.586	14.516
Service Customization	CC1	.571	.506	**.840**	.531	.524	.306	.181	.211	.177	.092	.255	.167	.285	.218	.206	.150	.084	.229	.194	.107	.590	26.002
	CC2	.321	.390	**.875**	.224	.602	.256	.154	.174	.143	.030	.158	.132	.230	.237	.173	.232	.055	.187	.026	.050	.748	24.531
	CC3	.371	.284	**.869**	.341	.580	.245	.133	.200	.124	.085	.163	.129	.264	.223	.199	.241	.019	.206	.062	.058	.737	22.844
Availability	CA1	.639	.495	.375	**.817**	.340	.268	.227	.265	.140	.209	.294	.144	.278	.178	.257	.121	.009	.214	.213	.173	.570	19.229
	CA2	.503	.441	.262	**.853**	.243	.209	.173	.211	.154	.186	.249	.129	.211	.087	.169	-.010	.048	.181	.308	.207	.685	11.106
	CA3	.508	.385	.465	**.873**	.469	.186	.189	.220	.166	.168	.245	.154	.240	.150	.195	.079	-.018	.191	.223	.161	.694	17.379
Scalability	CS1	.456	.370	.633	.446	**.866**	.264	.243	.201	.253	.070	.196	.188	.341	.312	.197	.239	.038	.208	.158	.117	.686	27.063
	CS2	.372	.359	.560	.325	**.903**	.308	.152	.133	.188	.019	.146	.083	.293	.243	.180	.273	.050	.232	.150	.097	.788	29.472
	CS3	.331	.384	.574	.353	**.925**	.279	.146	.137	.161	.021	.146	.096	.316	.225	.181	.202	.029	.218	.152	.135	.835	30.709
Pay Per Use	CP1	.369	.273	.254	.275	.250	**.882**	.115	.072	.088	.076	.099	.083	.199	.167	.129	.103	.037	.084	.138	.026	.559	9.323
	CP2	.367	.351	.278	.341	.275	**.911**	.212	.138	.160	.147	.114	.172	.207	.190	.155	.120	.023	.091	.130	.048	.615	11.262
	CP3	.024	.030	.251	-.065	.264	**.606**	-.043	-.132	-.071	-.014	-.120	.067	.072	.095	-.020	.120	-.007	-.071	-.120	-.125	.583	2.837
	CP4	.062	.050	.217	.048	.219	**.633**	-.025	-.089	-.019	.039	-.068	.032	.112	.133	.001	.098	.023	.036	.011	-.049	.605	2.859
EHR Characteristics																							
Interoperability	EI2	.189	.117	.033	.179	.086	.157	**.780**	.393	.475	.570	.410	.501	.310	.196	.281	.152	.029	.028	.120	.104	.638	10.057
	EI3	.260	.266	.211	.243	.215	.120	**.881**	.699	.642	.483	.647	.553	.428	.319	.422	.260	.082	.141	.161	.146	.763	27.976
	EI4	.223	.204	.150	.219	.171	.071	**.864**	.587	.540	.469	.568	.537	.321	.258	.366	.232	.061	.111	.092	.087	.752	18.207
	EI5	.199	.200	.201	.143	.195	.092	**.835**	.659	.647	.510	.570	.621	.337	.307	.363	.287	.064	.188	.112	.100	.673	20.665
Longitudinal	EL1	.303	.307	.232	.278	.181	.078	.710	**.940**	.618	.548	.772	.563	.366	.277	.413	.215	.028	.223	.249	.190	.816	80.992
	EL2	.291	.306	.197	.305	.156	.052	.647	**.947**	.597	.563	.777	.520	.349	.257	.425	.195	.034	.248	.283	.251	.840	72.008
	EL3	.191	.165	.184	.142	.136	-.008	.530	**.802**	.569	.356	.595	.446	.262	.262	.342	.236	.022	.225	.154	.161	.631	12.476
Granularity	EG2	.273	.257	.163	.213	.154	.071	.570	.643	**.810**	.413	.618	.388	.271	.291	.407	.235	.020	.151	.259	.230	.533	18.606
	EG3	.169	.134	.139	.118	.206	.152	.434	.374	**.761**	.483	.412	.478	.226	.261	.289	.269	.031	.080	.100	.076	.527	12.289
	EG4	.159	.162	.121	.104	.190	.011	.644	.555	**.842**	.421	.553	.563	.308	.296	.309	.216	.104	.108	.190	.157	.586	23.596
Stand. Logical Information	ES2	.119	.073	.044	.171	.027	.115	.552	.436	.439	**.891**	.517	.562	.223	.175	.236	.123	-.005	.133	.126	.093	.774	15.128
	ES3	.192	.158	.093	.233	.056	.081	.573	.550	.564	**.953**	.609	.625	.279	.221	.340	.175	.008	.142	.160	.127	.880	59.192
	ES4	.201	.163	.089	.209	.032	.089	.542	.542	.493	**.934**	.643	.551	.308	.235	.383	.159	.032	.130	.192	.152	.840	43.788
Persistence of Information	EP1	.294	.268	.196	.289	.140	.033	.610	.714	.598	.599	**.839**	.535	.291	.311	.352	.197	.083	.239	.282	.260	.578	24.673
	EP2	.269	.260	.204	.247	.171	.052	.575	.700	.624	.552	**.876**	.514	.345	.328	.367	.248	.099	.237	.261	.237	.756	23.422
	EP3	.315	.280	.229	.319	.189	.069	.630	.789	.604	.606	**.864**	.612	.367	.312	.434	.261	.047	.244	.260	.227	.746	16.288
Completeness of Information	EC1	.212	.201	.159	.171	.109	.121	.686	.670	.569	.521	.651	**.897**	.405	.318	.439	.293	.026	.139	.169	.133	.772	23.612
	EC2	.104	.105	.107	.128	.103	.095	.487	.394	.453	.604	.465	**.922**	.246	.135	.214	.147	-.020	.068	.046	.020	.824	22.238
	EC3	.071	.093	.164	.128	.148	.113	.490	.352	.484	.486	.402	**.935**	.250	.150	.218	.196	.003	.062	-.019	-.037	.843	51.315
SaaS-EHR Matching																							
	CM1	.258	.275	.316	.210	.368	.238	.357	.323	.274	.208	.290	.299	**.862**	.434	.353	.477	.151	.216	.207	.136	.821	25.021
	CM2	.328	.243	.294	.271	.322	.226	.409	.371	.348	.271	.365	.339	**.901**	.435	.425	.417	.130	.216	.266	.196	.869	28.477
	CM3	.255	.182	.250	.266	.305	.153	.389	.337	.309	.245	.352	.314	**.895**	.411	.416	.424	.147	.189	.231	.149	.863	28.231
	CM4	.261	.230	.265	.229	.345	.212	.342	.285	.252	.198	.287	.262	**.881**	.421	.371	.465	.123	.188	.190	.104	.847	26.006
	CM6	.260	.207	.268	.263	.331	.211	.374	.324	.278	.243	.311	.320	**.913**	.410	.422	.377	.137	.210	.245	.164	.886	35.201
	CM7	.304	.253	.295	.282	.312	.174	.364	.333	.279	.277	.349	.329	**.921**	.416	.419	.363	.150	.244	.295	.197	.898	39.841
	CM8	.301	.233	.275	.290	.302	.156	.327	.321	.302	.250	.337	.282	**.892**	.390	.408	.313	.108	.214	.267	.193	.863	29.287
	CM9	.240	.177	.238	.230	.260	.151	.373	.307	.302	.336	.280	.366	**.863**	.369	.431	.377	.035	.185	.181	.108	.829	16.999
	CM10	.292	.222	.226	.267	.276	.142	.399	.318	.339	.318	.339	.371	**.865**	.358	.431	.302	.052	.177	.224	.136	.832	16.947
Stakeholder Benefits																							
Patient & Medical Personnel Benefits	SP1	.176	.171	.210	.127	.214	.179	.312	.221	.286	.175	.257	.228	.371	**.839**	.454	.572	.098	.118	.146	.093	.793	20.701
	SP2	.110	.139	.165	.099	.206	.155	.288	.243	.310	.184	.280	.203	.367	**.843**	.377	.519	.107	.115	.139	.103	.803	25.279
	SP3	.244	.203	.224	.196	.227	.153	.325	.303	.308	.231	.351	.213	.437	**.825**	.527	.506	.053	.124	.280	.186	.767	19.119
	SP4	.164	.150	.200	.136	.216	.125	.186	.179	.249	.174	.270	.138	.321	**.798**	.322	.446	.088	.138	.158	.132	.750	16.174
	SP5	.117	.131	.157	.069	.204	.154	.246	.176	.290	.150	.256	.167	.322	**.851**	.393	.545	.106	.096	.109	.060	.811	25.069
	SP6	.259	.199	.217	.208	.240	.132	.316	.294	.323	.257	.363	.210	.406	**.768**	.497	.471	.022	.109	.227	.128	.702	14.037
	SP7	.222	.205	.261	.181	.283	.172	.335	.303	.338	.282	.352	.301	.431	**.840**	.499	.536	-.025	.124	.184	.174	.790	19.269
	SP8	.199	.186	.308	.118	.311	.209	.242	.246	.267	.153	.221	.214	.356	**.793**	.342	.455	.035	.162	.140	.149	.745	14.029
	SP9	.213	.115	.203	.119	.260	.142	.149	.195	.226	.122	.243	.109	.365	**.773**	.339	.418	.030	.212	.217	.152	.727	13.595
	SP10	.150	.185	.198	.098	.222	.174	.222	.229	.257	.117	.204	.195	.337	**.807**	.357	.546	.104	.212	.158	.150	.767	19.454
Hospital Benefits																							
Cost Efficiency	SH6	.280	.203	.196	.219	.192	.095	.420	.420	.388	.262	.380	.303	.387	.476	**.888**	.534	.002	.175	.210	.204	.822	27.677
	SH7	.238	.170	.195	.214	.193	.105	.365	.395	.403	.249	.353	.287	.342	.431	**.880**	.520	.037	.187	.262	.197	.811	30.081
	SH8	.328	.250	.253	.296	.226	.092	.397	.406	.356	.315	.376	.309	.424	.489	**.892**	.550	-.008	.204	.213	.184	.828	29.578
	SH9	.253	.198	.176	.179	.177	.133	.369	.380	.368	.347	.383	.350	.446	.421	**.904**	.573	.024	.204	.226	.167	.844	28.322
	SH10	.228	.143	.178	.188	.132	.097	.353	.348	.342	.368	.369	.314	.438	.435	**.872**	.539	.020	.204	.185	.167	.795	27.306
Work Efficiency	SH1	.063	.062	.190	.046	.153	.096	.205	.196	.199	.149	.221	.159	.262	.264	.330	**.626**	.085	.173	.094	.141	.529	7.392
	SH2	.115	.171	.189	.136	.259	.153	.238	.200	.245	.149	.237	.200	.334	.400	.399	**.737**	.118	.151	.131	.135	.637	12.532
	SH11	-.003	.028	.155	-.038	.182	.104	.163	.095	.195	.000	.088	.102	.317	.504	.462	**.811**	.021	.159	.027	.059	.714	16.929
	SH12	.111	.101	.219	.112	.213	.100	.225	.231	.264	.180	.277	.270	.388	.503	.529	**.809**	.006	.177	.025	.030	.694	18.538
	SH13	.075	.115	.182	.055	.207	.107	.247	.210	.234	.149	.201	.238	.391	.601	.543	**.882**	.108	.178	.146	.135	.793	42.431
	SH14	.112	.094	.192	.067	.238	.094	.253	.196	.258	.161	.204	.224	.375	.580	.587	**.837**	.092	.190	.109	.086	.723	24.166
Privacy Concern																							
Collection	PC1	-.029	.015	.041	.004	.028	.016	.031	.011	.078	-.019	.050	-.021	.105	.067	.023	.108	**.879**	.230	.228	.294	.768	22.995
	PC2	.008	.043	.052	-.002	.049	.005	.036	.005	.029	-.016	.038	-.017	.091	.063	.005	.075	**.911**	.253	.207	.281	.825	30.4884
	PC3	.063	.098	.072	.029	.038	.048	.109	.057	.067	.055	.116	.040	.143	.071	.016	.061	**.879**	.358	.399	.378	.667	43.864
Errors	PE1	.178	.111	.181	.223	.210	-.001	.197	.332	.151	.185	.298	.161	.239	.161	.241	.215	.194	**.839**	.425	.448	.626	23.8006
	PE2	.246	.187	.220	.243	.230	.100	.109	.195	.095	.137	.229	.060	.216	.134	.161	.142	.286	**.848**	.477	.466	.615	20.4173
	PE3	.107	.103	.201	.103	.164	.071	.050	.111	.110	.036	.118	.051	.113	.131	.145	.186	.327	**.798**	.361	.446	.569	14.9986
Unauthorized Access	PU1	.175	.219	.085	.202	.143	.064	.075	.145	.147	.104	.167	.029	.194	.152	.158	.076	.360	.458	**.774**	.552	.631	12.1353
	PU2	.222	.185	.124	.217	.138	.103	.099	.182	.170	.137	.217	.080	.214	.175	.189	.085	.305	.402	**.881**	.657	.777	13.6841
	PU3	.306	.226	.103	.286	.145	.076	.135	.266	.216	.153	.290	.071	.248	.198	.253	.102	.263	.443	**.936**	.733	.854	52.5269
	PU4	.360	.244	.103	.304	.174	.090	.193	.306	.278	.209	.340	.122	.271	.231	.261	.126	.235	.497	**.923**	.742	.829	66.5766
Secondary Use	PS1	.144	.124	.074	.088	.110	-.002	.142	.205	.168	.120	.214	.033	.186	.128	.188	.101	.384	.503	.605	**.882**	.583	23.3104
	PS2	.297	.259	.079	.282	.120	.001	.092	.196	.183	.120	.252	.063	.125	.160	.180	.112	.268	.471	.753	**.897**	.583	30.9982

ITO: Item to total

Table 4 *Reliability, convergent and discriminant validity*

Constructs	AVE	C.R.	α	CR	CD	CC	CA	CS	CP	EI	EL	EG	ES	EP	EC	CM	SP	SH-c	SH-w	PC	PE	PA	PS
Reusability (CR)	.724	.913	.873	**.851**[a]																			
Data Managed by Provider(CD)	.673	.861	.757	.669	**.821**[a]																		
Service Customization(CC)	.742	.896	.828	.503	.467	**.861**[a]																	
Availability (CA)	.719	.885	.805	.652	.520	.439	**.848**[a]																
Scalability (CS)	.807	.926	.880	.433	.413	.658	.420	**.898**[a]															
Pay Per Use(CP)	.594	.850	.786	.330	.283	.316	.262	.316	**.770**[a]														
Interoperability (EI)	.707	.906	.862	.260	.238	.183	.233	.203	.129	**.841**[a]													
Longitudinal (EL)	.808	.926	.879	.296	.294	.228	.275	.176	.049	.605	**.899**[a]												
Granularity (EG)	.648	.846	.728	.250	.232	.175	.181	.226	.090	.590	.660	**.805**[a]											
Std. Logical Information (ES)	.858	.948	.917	.186	.144	.082	.222	.042	.102	.600	.552	.540	**.926**[a]										
Persistence of Information (EP)	.739	.895	.825	.158	.162	.168	.169	.139	.129	.659	.570	.591	.626	**.859**[a]									
Completeness of Information(EC)	.843	.942	.907	.319	.294	.228	.311	.182	.056	.659	.601	.662	.638	.604	**.918**[a]								
SaaS-EHR Matching(CM)	.789	.971	.967	.313	.254	.304	.289	.354	.209	.417	.366	.336	.293	.360	.364	**.888**[a]							
Patient & Medical Personnel (SP)	.663	.952	.943	.227	.207	.262	.166	.292	.196	.325	.294	.352	.228	.245	.345	.457	**.814**[a]						
Cost Efficiency (SH-c)	.787	.949	.932	.299	.218	.225	.247	.208	.118	.430	.439	.418	.348	.353	.420	.460	.507	**.887**[a]					
Work Efficiency (SH-w)	.621	.907	.876	.100	.120	.237	.079	.265	.136	.281	.237	.295	.166	.255	.257	.441	.618	.613	**.788**[a]				
Collection (PC)	.792	.919	.871	.021	.064	.064	.014	.043	.029	.072	.031	.066	.013	.005	.082	.131	.076	.017	.089	**.890**[a]			
Errors (PE)	.686	.868	.772	.217	.163	.243	.232	.244	.069	.144	.257	.142	.146	.109	.261	.230	.171	.220	.217	.324	**.828**[a]		
Unauthorized Access(PU)	.776	.932	.902	.306	.248	.118	.289	.171	.095	.145	.259	.233	.173	.087	.291	.264	.216	.247	.112	.327	.511	**.881**[a]	
Secondary Use(PS)	.791	.883	.736	.251	.218	.086	.211	.130	.000	.131	.225	.197	.120	.055	.262	.174	.162	.207	.135	.364	.547	.666	**.889**[a]

Notes: a= Square roots of AVE; AVE= Average Variance Extracted; C.R.= Composite Reliability

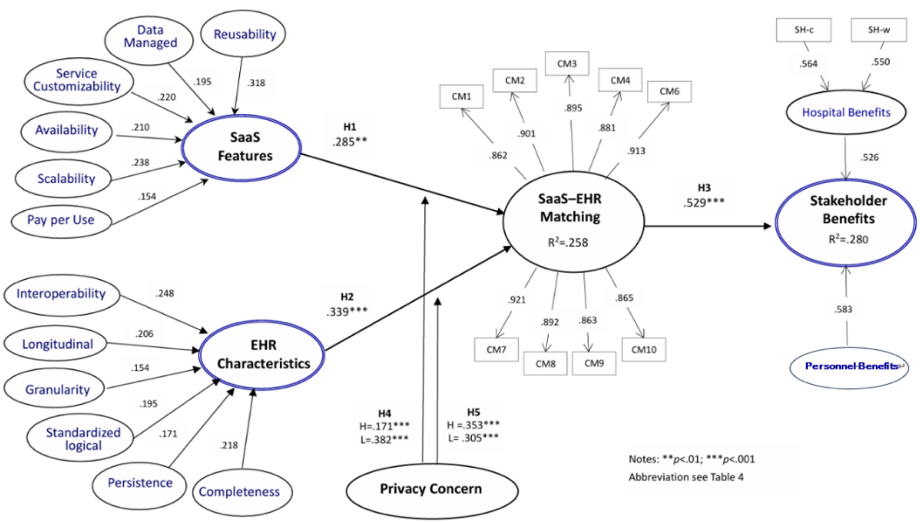

Fig. 2 *Results of PLS-SEM*

Table 5. *Formation Weight Aggregates*

Constructs	Dimensions/ Items	Weights	t-value	VIF
SaaS Features	Reusability	.318	12.398	2.422
	Data Managed by Provider	.195	9.870	1.883
	Service Customization	.220	9.412	1.970
	Availability	.210	8.008	1.828
	Scalability	.238	8.452	1.900
	Pay Per Use	.154	4.202	1.150
EHR Characteristics	Interoperability	.248	12.788	2.639
	Longitudinal	.206	12.151	3.167
	Granularity	.154	8.608	2.223
	Std. Logical Information Model	.195	12.481	2.108
	Persistence of Information	.171	10.573	2.041
	Completeness Information	.218	13.657	3.352
Stakeholder Benefits	Hospital	.526	16.073	1.637
	Patient & Medical Personnel	.583	19.097	1.637
Hospital	Cost Efficiency	.564	18.875	1.572
	Work Efficiency	.550	20.988	1.572

Table 6 *Results of Hypothesis Testing – Main Effects and Moderating Effects*

Hypothesis – Main effects	Stand Coefficients		t-test	Results
H1. SaaS Features → SaaS-EHR Matching	.285**		3.083	Supported
H2. EHR Characteristic → SaaS-EHR Matching	.339***		4.772	Supported
H3a. SaaS-EHR Matching → Hospital Benefits	.522***		8.020	Supported
H3b. SaaS-EHR Matching → Patients & Medical Personnel	.538***		8.118	Supported
Moderating effects: Privacy Concern	High-PC (N=219)	Low-PC (N=137)	t-test	Results
H4. Privacy Concern → SaaS Features to SaaS-EHR Matching	.171**	.382***	1.972	Supported
H5. Privacy Concern → EHR Characteristic to SaaS-EHR Matching	.353***	.305***	0.507	Not supported

Notes: *p<.05; **p<.01; ***p<.001

5. Discussion and Conclusions

5.1. Discussion

The main objective of this study was to develop a conceptual framework and empirically test whether SaaS features and EHR characteristics can be matched when health institutes adopt cloud technology. Stakeholder benefits were evaluated, with privacy concern as a moderator. Results showed positive relationships between SaaS features, EHR characteristics, and matching, supporting H1 and H2 (Schweitzer, 2012; Chen et al., 2016; Gao et al., 2011; Xu et al., 2017). H3 was also supported, consistent with prior studies (Kohli & Tan, 2016; Xu et al., 2017; Menachemi & Collum, 2011; Mildon & Cohen, 2001). Cloud-based EHRs reduce printing costs, improve decision accuracy, and lower malpractice risks (Chen et al., 2016; Singh & Sitting, 2016; Virapongse et al., 2008), while enhancing coordination and service value for patients (Rahman & Reddy, 2015; Wang & Lin, 2019). Overall, organizational benefits such as cost reduction and revenue gains were more evident than individual benefits. Regarding moderation, only H4 was supported: patients with higher privacy concern expressed less confidence in cloud data security (Rodrigues et al., 2013; Angst & Agarwal, 2009; Yang & Lin, 2015). H5 was not supported, as both high- and low-privacy concern groups evaluated SaaS–EHR matching similarly. According to privacy calculus theory, patients viewed accurate health information for better care as outweighing privacy risks (Li et al., 2016). Overall, most of the proposed hypotheses were supported, only one hypothesis is not supported. The EHR and the implementation of SaaS indeed demonstrated a matching effect between their characteristics. This integration of SaaS and EHR also generated tangible benefits for stakeholder (i.e., hospitals, patient and medical personnel). Finally, the results reveal that privacy concerns exerted a significant moderating effect on the integration of SaaS-EHR from the user perspective, whereas this moderating effect did not exist in the process of matching EHR systems with SaaS. These results suggest that medical institutions, cloud providers, and regulators should adopt explicit carrot-and-stick mechanisms. Incentives may include support for upgrades, implementation, and training, while safeguards require clear regulations on data collection, maintenance, and protection. Such measures ensure technological advancements in data management enhance stakeholder benefits while mitigating risks.

5.2 Theoretical Implications

This study provides several theoretical implications. Firstly, it contributes to SaaS–EHR literature by developing formative constructs and empirically validating their matching; all formative weights were significant at the 95% confidence level, with scales showing good reliability and validity (Armbrust et al., 2010; Hoerbst & Ammenwerth, 2010; ISO, 2005). Secondly, by applying resource-matching theory (RMT), the study extends its application from alliances (Mitsuhashi & Greve, 2009), decision performance (Tan et al., 2010), and task presentation (Giboney et al., 2015) to healthcare and cloud computing, demonstrating how SaaS supports EHRs to enhance services and care quality. Thirdly, organizational and individual benefits were confirmed, as EHRs reduce costs, improve processes, and indirectly increase hospital revenue (Rahman & Reddy, 2015). Lastly, while privacy concern has been emphasized in cloud computing (Yang & Lin, 2015) and EHR research (Li et al., 2016), this study shows it is more salient in SaaS–EHR matching, contributing to privacy calculus theory by revealing patients seeking higher-value care are more willing to disclose information.

5.3 Managerial Implications

This study provides several managerial implications. Based on the finding, the study offers hierarchical, managerial implication which begins at the local level, extending to the regional level, and ultimately scaling to the national level. From the local perspective, integrating EHR with SaaS enhances information sharing, reduces redundant exams and errors, and improves timeliness in emergencies by streamlining communication and lowering information asymmetry. Administrators should assess departmental needs to design customized EHRs, train staff to guide patients, and partner with credible providers while clearly communicating security and privacy policies to build trust. Encouraging patient participation in daily data entry can ease adoption. At a broader level, cloud-based healthcare analytics and business intelligence enable large-scale data analysis and AI-driven modeling for epidemic surveillance, clinical trials, and precision medicine, highlighting the potential of cloud-enabled EHRs to advance evidence-based decision-making and healthcare innovation.

From the regional perspective, SaaS–EHR integration enhances data exchange across hospitals and healthcare networks. Local administrative offices should oversee and promote adoption by establishing privacy regulations, standardizing information models, and providing protection schemes and subsidies. These measures improve interoperability, strengthen data governance, aid disease-tracing, and reduce infection risks. For patients, combining SaaS–EHR with patient relationship management systems centralizes records and links them with mobile apps, enabling real-time access, reminders, and personalized health tips. This improves adherence, follow-ups, and trust, ultimately supporting a patient-centered care model that enhances healthcare experiences and long-term outcomes.

From the national perspective, the successful integration of SaaS–EHR relies on robust regulatory frameworks. Authorities should enforce cross-border data governance, harmonized standards, and strong security frameworks to reduce breach risks. Regulations must reinforce patient consent, data ownership, and vendor liability for leakage or misuse, while also clarifying acceptable secondary uses of health records in AI. Cloud providers should ensure robust infrastructure, firewalls, authentication, and 24-hour monitoring to maintain stability and prevent data loss. Together, these measures lower privacy concerns, enhance transparency, and support sustainable SaaS–EHR adoption at the national level.

5.4 Limitations and Directions for Future Research

This study has several limitations. Firstly, the study classified stakeholders into organizations and individuals, with the latter including both patients and medical personnel. Owing to most respondents were medical personnel and patients accounted for only a small share, they were not analyzed separately. Nonetheless, as EHR use increasingly involves patients, and their considerations likely differ from those of medical personnel. Future research is suggested to extend this framework by distinguishing these two groups and exploring the potential mechanisms that drive patient and medical personnel adoption of SaaS-EHR systems. Secondly, most respondents were from Northern Taiwan; broader regional samples would provide a more comprehensive view of medical personnel's perceptions. Thirdly, this study merely focused on the benefits of SaaS-EHR for key stakeholders. Future research may extend this empirical framework to examine additional outcomes such as healthcare delivery, particularly its timeliness and efficiency, and clinical performance. Fourthly, this study adopted a cross-sectional framework. As SaaS and EHRs evolve, future research should apply longitudinal designs and case studies to better capture practices and user perspectives on information security. Finally, the study mainly focused on the matching effect between SaaS and EHR. However, the rise of AI and blockchain has reshaped data structures. Future research could explore how AI's demand for large-scale data integration and blockchain's emphasis on decentralization and security jointly influence user experience and adoption in healthcare contexts.

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