Factors Influencing the Use of Health Information Systems by Health Professionals

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Abstract. Although Health Information Systems (HIS) are increasingly being used in healthcare settings, the factors that influence their adoption and the intricate relationships between these factors remain unclear due to the distinctive characteristics of healthcare environments. This study seeks to investigate the factors contributing to healthcare professionals' intention to use HIS and explain the nature of the relationships between these factors. Data was gathered from 109 healthcare professionals in various healthcare settings in Indonesia. Structural Equation Modeling (SEM) was conducted using STATA. The findings indicate a positive association between Performance Expectancy and Collaboration Skills with Social Influence, which, in turn, positively influences the intention to use HIS. The perceived ease of mastering and using the system also influences the intention to use HIS. Finally, the actual behaviour of HIS usage is directly influenced by the intention to use and facilitating conditions.

Keywords: health information system; UTAUT; communication; collaboration

1 Introduction

Health information systems (HIS) are increasingly used in healthcare organizations to improve the efficiency and quality of patient care [1]. HIS can help automate administrative tasks, improve communication between healthcare professionals, and provide access to patients' medical records [2]. However, healthcare professionals' adoption and use of HIS have been slow in some cases [3].

Prior research has demonstrated that the adoption and use of hospital information systems (HIS) is influenced by several factors, including perceived usefulness, perceived ease of use, and social influence [4]–[6]. However, as digital collaboration becomes increasingly prevalent among health professionals, some of these factors may change, which could, in turn, impact the behavioural intention of health professionals to use HIS.

Despite the growing importance of Health Information Systems (HIS) and the increasing emphasis on digital solutions, there exists a noticeable gap in the understanding of how digital communication and collaboration skills of health professionals impact the utilization of HIS. While previous studies have explored the broader concepts of digital literacy and health informatics, there is a lack of in-depth analysis focusing on the nuanced interrelation between these competencies and the use of HIS. Furthermore, existing literature often overlooks the contextual factors that influence the development and application of these skills within diverse healthcare settings. Addressing this gap is crucial for devising targeted strategies that can

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enhance the utilization of HIS among health professionals, thereby improving the overall quality of healthcare services.

This research explores the inter-relationship between digital communication, collaboration effectiveness, and various elements of UTAUT, such as perceived usefulness, perceived ease of use, social influence, and facilitating conditions. It focuses on the intention to use and the actual use of Health Information Systems (HIS). The results of the study offer valuable perspectives on the factors shaping healthcare professionals' adoption of HIS. Additionally, it sheds light on the intricate relationships among these factors, providing insights that can inform the development of interventions to encourage the uptake and utilization of HIS in hospital settings.

2 Method and Materials

This study surveyed various health professionals from many different healthcare settings, ensuring the inclusion of a broad spectrum of captured data [7]. Participants are recruited through the researcher's personal and professional networks through social media. Participation in this research is voluntary. Data was collected using an online survey form administered through LimeSurvey. The survey form included questions to measure digital communication and collaboration skills, perceived usefulness, perceived ease-of-use, social influence, facilitating conditions, behavioural intention to utilize hospital information systems, and the actual use of HIS. The survey form also included the demographic and professional characteristics of the participants. A total of 215 responses were acquired.

Nevertheless, after applying specific inclusion criteria, the study encompasses 109 participants who satisfy these criteria. Data was analysed using structural equation modelling (SEM). SEM is a statistical technique that allows for estimating multiple relationships between variables. In this study context, SEM was used to test various hypotheses, as depicted in Figure 1. All analyses were conducted with the aid of STATA.

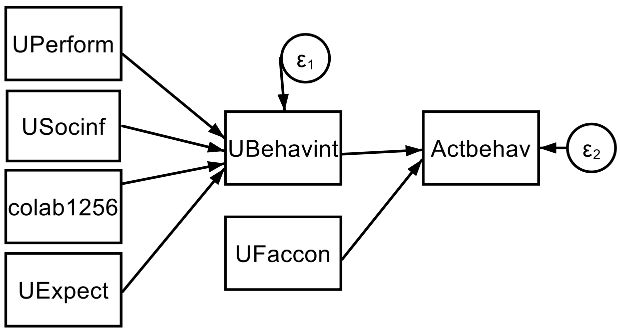

Fig. 1. Initial Conceptual Model.

The conceptual model comprises seven variables. *UPerform* (Performance expectancy) signifies the perceived usefulness, *and UExpect* (Effort expectancy) denotes the health professionals' perception of the ease with which they can learn and use the system. *USOCinf* (Social influence) represents the influence of colleagues, and *UFaccon* (Facilitating condition) represents the conditions surrounding the system. *Colab1256* (Collaboration Skill) signifies the efficacy of communication and collaboration on a digital platform among health professionals, *UBehavint* (Intention to use) denotes the intention to use the system, and finally, *Actbehav* (Actual use behaviour) represents the practical utilization of the system.

3 Results and Discussion

3.1 Demographic Profile

The educational backgrounds of the individuals surveyed are diverse, encompassing three major categories: diploma, graduate, and postgraduate. A substantial portion, constituting 47.71%, holds a Diploma. Nearly as prevalent, with 46.79%, are those with a Graduate degree, suggesting a considerable emphasis on higher education. In contrast, the smallest fraction, comprising 5.50%, possesses a postgraduate qualification, highlighting the relatively lower prevalence of individuals with advanced degrees in the sample cohort.

Table 1. Demographic profile

	Freq	*Per cent*	*Cum*
Education			
Diploma	52	47.71	47.71
Graduate	51	46.79	94.50
Post Graduate	6	5.50	100.00
Sex			
Female	77	70.64	70.64
Male	32	29.36	100.00
Nature of Work			
Management	16	14.68	14.68
Technical	93	85.32	100.00

Gender distribution within the group reveals an interesting dynamic. The majority, constituting 70.64%, identify as female, while the remaining 29.36% identify as male. The nature of work undertaken by individuals in the group is divided into two categories: management and technical. Notably, 14.68% are engaged in managerial roles, indicating the presence of individuals responsible for overseeing and coordinating various aspects of health information system implementation. Conversely, 85.32% of the group is involved in technical roles, emphasizing a strong orientation towards tasks such as the real application of the health information system. This distribution sheds light on the occupational composition of the respondents.

3.2 The Initial Conceptual Model

We analysed the initial conceptual model. In this first analysis, we found structural issues in the model. Some relationships were not confirmed, and the overall model likelihood differed from the saturated model, as shown in Table 2.

Table 2. Structural model statistics

	Coefficient	std. err.	z	P>|z|	[95% conf. interv]	
Structural						
UBehavint						
USocinf	0.291147	0.054806	5.31	0.000	0.183729	0.398566
UPerform	-0.01253	0.059797	-0.21	0.834	-0.12973	0.104666
Colab1256	0.060097	0.040041	1.50	0.133	-0.01838	0.138576
UExpect	0.16166	0.067858	2.38	0.017	0.028661	0.294659
_cons	2.698042	1.004823	2.69	0.007	0.728624	4.667460
Actbehav						
UBehavint	0.564468	0.080871	6.98	0.000	0.405964	0.722973
UFaccon	0.198882	0.059555	3.34	0.001	0.082157	0.315607
_cons	2.092572	0.899934	2.33	0.020	0.328734	3.856410
var(e.UBehavint)	1.619829	0.219417			1.242133	2.112373
var(e.Actbehav)	1.518747	0.205725			1.164620	1.980554

LR test of model vs. saturated: chi2(5) = 7.79 Prob > chi2 = 0.1681

The conceptual model did not align well with the data. The structural model presented above indicates that two relationships lack significance; specifically, performance expectancy does not exhibit a correlation with Intention Behavior (p = 0.834 > 0.05), and similarly, collaboration skill is not significantly correlated with intention behaviour (p = 0.133 > 0.05). Additionally, the Likelihood ratio test of the model suggests that the overall model does not significantly differ from the saturated model, indicating that the conceptual model is not particularly useful.

The resulting model is depicted in Figure 2.

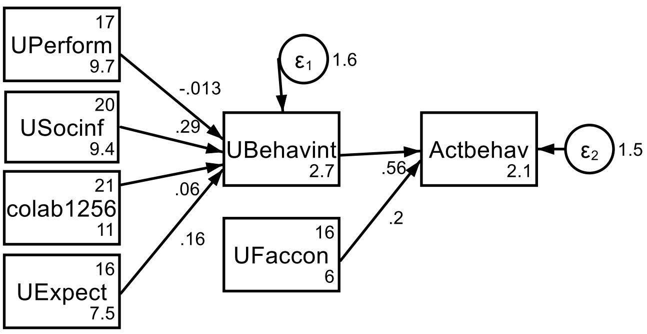

Fig. 2. The initial model

We run a pairwise analysis to further analyse the correlation between all variables, as shown in the correlation matrix in the following table.

The correlation matrix of the variables is presented in Table 3.

Table 3. Correlation matrix

Item	UPerform	UExpect	USocinf	UFaccon	col~1256	UBehav~t	Actbehav
UPerform	1.000						
UExpect	0.7176*	1.000					
	0.0000						
USocinf	0.6297*	0.6214*	1.000				
	0.0000	0.0000					
UFaccon	0.5995*	0.7219*	0.6514*	1.000			
	0.0000	0.0000	0.0000				
colab1256	0.2735	0.3238*	0.3397*	0.3510*	1.000		
	0.0840	0.0125	0.0063	0.0038			
UBehavint	0.4964*	0.5733*	0.6713*	0.5862*	0.3511*	1.000	
	0.0000	0.0000	0.0000	0.0000	0.0038		
Actbehav	0.5110*	0.5316*	0.6345*	0.5898*	0.3335*	0.7093*	1.000
	0.0000	0.0000	0.0000	0.0000	0.0083	0.0000	

As depicted in the table above, there is a significant correlation among all variables except for collaboration skill, which exhibits no statistically significant correlation with performance expectancy (correlation coefficient: 0.2735, $p=0.08 > 0.05$). Since there was no theoretical foundation supporting the association between collaboration skills and performance expectancy, we opted to exclude it from the model. We also removed the path from Uperform to Ubehavint due to statistical reasons.

3.3 The Final Model

We explored and examined various models to identify the most suitable data representation. Once a model was estimated, we gathered additional information regarding its fit, parameter estimates, and other pertinent statistics, including the Comparative Fit Index (CFI) and Root Mean Square Error of Approximation (RMSEA). We also examined the modification indices to identify the potential improvement in the model fit by allowing specific parameters to be freely estimated. After many attempts, the model was developed.

Table 4. Structural equation model (Estimation method: maximum Likelihood)

	Coefficient	std. err.	z	P>z	[95%	interval]
Structural						
USocinf						
UPerform	0.571672	0.07428	7.70	0.000	0.426086	0.717258
colab1256	0.169220	0.070503	2.40	0.016	0.031037	0.307404
_cons	7.171776	1.675382	4.28	0.000	3.888088	10.45546
UBehavint						
USocinf	0.301834	0.051329	5.88	0.000	0.201231	0.402436
UExpect	0.167292	0.057391	2.91	0.004	0.054808	0.279775
_cons	3.447277	0.876245	3.93	0.000	1.729868	5.164687
Actbehav						
UBehavint	0.564468	0.080871	6.98	0.000	0.405964	0.722973
UFaccon	0.198882	0.059555	3.34	0.001	0.082157	0.315607
_cons	2.092572	0.899934	2.33	0.020	0.328734	3.85641
var(e.USocinf)	5.378053	0.728495			4.124049	7.013364
var(e.UBehavint)	1.653963	0.224041			1.268308	2.156886

var(e.Actbehav)	1.518747	0.205725			1.16462	1.980554

LR test of model vs. saturated: chi2(9) = 31.02 Prob > chi2 = 0.0003
The structural equation shows that each variable has a positive relationship.

The likelihood ratio (LR) test compares the fit of the specified model to a saturated model (a model with the perfect fit). A significant chi-square value (Prob > chi2 < 0.05) suggests that the specified model fits significantly better than a model that perfectly predicts the observed data.

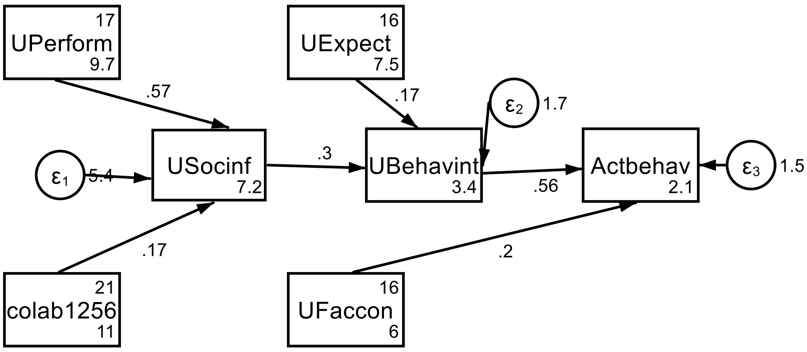

Fig. 3. The final model

The figure above shows the structural model. This model improves the initial model and is significantly better than the saturated model. We also have tested several competing models by analysing the model fit statistics. Table 5 displays the final model fit.

Table 5. Model fit test.

Fit statistic	Value	Description
Likelihood ratio		
chi2_ms(9)	31.018	model vs. saturated
p > chi2	0	
chi2_bs(15)	252.025	baseline vs. saturated
p > chi2	0	
Population error		
RMSEA	0.151	Root mean squared error of approximation
90% CI, lower bound	0.095	
upper bound	0.21	
pclose	0.003	Probability RMSEA <= 0.05
Information criteria		
AIC	3215.666	Akaike's information criterion
BIC	3247.962	Bayesian information criterion
Baseline comparison		
CFI	0.907	Comparative fit index

TLI	0.845	Tucker–Lewis index
Size of residuals		
SRMR	0.085	Standardized root mean squared residual
CD	0.536	Coefficient of determination

Based on the information from the above table, the model shows significant improvement over the saturated model based on the likelihood ratio test. The RMSEA suggests room for improvement, but the CFI and TLI values indicate an acceptable fit. These indices assess how well the model fits compared to a baseline model. Values close to 1 indicate a good fit. In this case, CFI is 0.907, which is generally considered acceptable.

Information criteria (AIC, BIC) provide additional measures of model fit and parsimony. The post estimate for this model is calculated for the Akaike's information criterion and Bayesian information criterion. AIC and BIC values are 3215.666 and 3247.962, respectively. These values are lower than those of the alternative model, which yields AIC 3323.989 and BIC 3364.359. The lower the AIC and BIC values, the better the trade-off between complexity and model fit.

The size of residuals (SRMR, CD) also suggests a reasonable fit. SRMR measures the average standardized difference between the observed and predicted correlations. Smaller values (closer to 0) indicate a better fit. In this case SRMR = 0.085. CD is the coefficient of determination, indicating the proportion of variance in the observed variables explained by the model. A higher value (closer to 1) is desirable. In this study, the CD value is 0.536. In summary, while the model shows areas for improvement, it generally fits the data reasonably well based on the provided fit indices.

The findings of this study indicate a positive association between Performance Expectancy and Collaboration Skills with Social Influence. Health professionals possessing strong digital communication and collaboration skills may utilize these skills personally and influence their peers to consider adopting Health Information Systems (HIS). This influence, in turn, positively affects the intention to use HIS. However, the perceived ease of mastering and using the system also influences the intention to use HIS. Finally, the intention to use and facilitate conditions directly impact the actual behaviour.

Communication and collaboration skills are essential in the context of using digital platforms, as these platforms often serve as the primary means of interaction and teamwork in various personal and professional settings [8], including in healthcare settings [9] and interprofessional collaboration [10]. Communicating effectively involves expressing ideas, thoughts, and information clearly and concisely. This skill is crucial in digital platforms where messages are transmitted through text, audio, video, or a combination. Digital communication often requires adapting to different platforms and mediums [11].

Working together on digital platforms requires individuals to contribute their skills and expertise to achieve common goals. This involves sharing responsibilities, coordinating efforts, and acknowledging the contributions of team members [12]. Proficiency with digital collaboration tools is essential. This includes project management software, video conferencing platforms, document-sharing tools, and other collaborative apps.

In contrast to other models that typically treat performance expectancy as an exogenous variable directly correlated with individuals' intention to use [5], [13], [14], our findings indicate that performance expectancy does not exhibit a direct correlation with behavioural intention. Instead, our model reveals that social influence is an intermediate variable between performance expectancy and the intention to use. This observation in our data may be attributed to the prolonged exposure of health professionals to the benefits of health information systems [15]. As they familiarize themselves with the system, they generally acknowledge its utility for their work. Moreover, there might be an implicit assumption that the use of information systems is beneficial [16]. However, the data suggests that they require some form of reinforcement, in this case, the influence of others, to actively engage with the system. All participants in this study are employed by at least one healthcare provider where there is a directive or obligation to use information systems. Despite their acknowledgement of the system's benefits, their usage is obligatory, and they rely on the influence of others to comply with this requirement.

Our study shows that health professionals are inclined to embrace Health Information Systems (HIS) when the system is user-friendly. This is consistent with many other studies investigating information systems and their interface [17]–[19]. A user-friendly information system is a system that is designed and implemented with the end user in mind, with the goal of making it easy, efficient, and enjoyable for users to interact with and use the system [20]. The term "user-friendly" emphasizes the importance of creating an interface and overall system experience that is intuitive, accessible, and responsive to user needs and preferences. This is reflected in our data. In other words, the motivation for healthcare professionals to interact with the system is driven by their perception of how easy it is to use and master the system. Consequently, a complex system is likely to reduce their inclination to use it. Given that social influence directly affects health professionals' intention to use HIS, enhancing the conditions related to these factors is likely to foster a more robust commitment to usage. Integrating social influence with an easy-to-use system would evidently enhance the Likelihood of health professionals intending to use the information system.

Implementation of a health information system within an organization or in a wider context has been proven to be beneficial [2], [21], [22]. Nevertheless, the advantages will materialize only through the successful implementation of the system. The employees' intention to use the system and their subsequent actions play a crucial role in ensuring its effective implementation. The utilization of the information system by healthcare professionals is contingent not only on the existence of intention but also on the presence of facilitating factors, encompassing digital and physical infrastructure, as well as regulatory and legal requirements essential for the system's operation. This aligns with findings from various other studies [23] that underscore the pivotal role of facilitating conditions [24], [25].

With the continuous progression of technology, nearly all employees have encountered digital aspects in their lives. Consequently, there is a rise in the level of individual digital literacy [26]. To ensure the success of a healthcare provider, it is imperative to furnish facilities, including digital infrastructure, that enable the implementation of its information system [15]. Many studies show even further impact of the digital world on people's health. For example, digital inclusion has been identified as one of the social determinants of health [27], [28]. This implies that a healthcare provider must prioritize equal inclusion of all its employees in the digital information system.

4 Conclusion

This research has illuminated the factors affecting the intention to utilize health information systems and their practical implementation, highlighting the interconnectedness among these factors. Communication and collaboration on digital platforms and performance expectations are linked to social influence, resulting in the intention to use. Additionally, effort expectation is associated to use. Both the intention to use and the presence of facilitating conditions significantly impact the utilization of the health information system.

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