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Examining the Acceptance of an Integrated Electronic Health Records System: Insights from a Repeated Cross-Sectional Design

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Abstract

Background and purpose: Hospital staff's acceptance of an integrated Electronic Health Records system (EHR) is a critical success factor to exploit the benefits EHRs can offer. This study employs a repeated cross-sectional design to differentiate between the enablers and barriers of EHR acceptance prior to EHR implementation and those that arise over time by testing a theoretical model specifically tailored to the EHR context.

Methods: A repeated cross-sectional design, consisting of one measurement of staff's acceptance before and two after EHR implementation, was employed in a Belgian hospital. To test the theoretical model, partial least squares structural equation modelling (PLS-SEM) was used. Furthermore, partial least squares multigroup analyses (PLS-MGA) and permutation tests were applied to examine whether the relations in the model vary significantly over time.

Results: The formulated model explains up to 80% of the variance in hospital staff's attitude towards the EHR. The extent to which the EHR leads to administrative simplification outperforms the core technology acceptance variables. Furthermore, support was found for the significant role of implementation factors (i.e. communication quality and training) and prior IT experiences in explaining EHR acceptance. Finally, the results show significant evolutions in path coefficients over time. An important trade-off between effort expectancy and performance expectancy was revealed, meaning effort expectancy is the most important determinant of hospital staff's attitude towards the EHR, but once the EHR has been implemented performance expectancy becomes more important.

Conclusions: The results of testing the hypothesized model reveal the importance of taking into account hospital staff's perception of the extent to which the EHR generates administrative simplification, a combination of implementation factors, and attitude towards technology in general when assessing the acceptance of an EHR. Moreover, the results highlight the importance of conducting repeated cross-sectional or longitudinal technology acceptance research as relations between core variables vary significantly over time, which implies hospital management and healthcare technology providers should adjust their policy throughout the various implementation stages.

1. Introduction

1.1 Context and objectives

In recent years, technology has become very important to health professionals and their patients. In 2013, the Belgian government launched an eHealth action plan with the purpose of stimulating the use of technology in healthcare, including administrative simplification and the implementation of hospital Electronic Health Record systems (EHRs) [1]. As a consequence of the initiative and the corresponding financial incentives, an increasing number of hospitals are currently implementing, or have recently implemented, an EHR.

As the new backbone of hospitals, EHRs have become of prime importance in healthcare since they transform both the administrative and the healthcare processes within hospitals and generally have numerous advantages over paper based health records or fragmented software packages in terms of quality of care, efficiency, and patient safety [2-6]. However, the extent to which these benefits are attained is highly variable between different healthcare institutions [7]. The reason for this can mainly be attributed to variations in hospital staff's acceptance of EHRs, in which the preferred implementation strategy and perceived system characteristics (e.g. the extent to which the EHR leads to administrative simplification) play a significant role [8]. Therefore, it is crucial to identify health professionals' attitudes towards EHRs, and the determinants of this attitude, to be able to tackle the remaining barriers to EHR acceptance and to fully unfold its potential benefits.

To date, however, most articles examining EHR acceptance use either qualitative or cross-sectional research designs. While a cross-sectional design may deliver insights into EHR acceptance at a given moment in time, the design fails to account for the time effects and the implementation stage which may play a significant role in explaining the acceptance of EHR systems. If the model's relations vary significantly over time, this would imply that hospital management and EHR providers should adjust their policy to each implementation stage. Despite the acknowledged value of longitudinal research in examining users' changing attitudes over time, Williams et al. found that 90% of the 174 examined studies was cross-sectional in nature [9]. Scholars repeatedly identify this caveat as one of the main shortcomings currently present in the research domain [10-12].

Furthermore, the existing body of EHR acceptance research largely fails to take into account the importance of administrative simplification due to the EHR and the role of a specific combination of implementation factors (such as training and communication quality) in explaining EHR acceptance. This article therefore examines the acceptance of an EHR and its evolution over time using a modified model of technology acceptance using unique primary survey data from a Belgian hospital in a repeated cross-sectional design. The hospital, in contrast to most hospitals, opted for a "big bang" implementation strategy in which the transition from 45 fragmented systems to the integrated EHR took place in a single day. This creates a unique context, in which the acceptance of the EHR is of ultimate importance.

1.2 Theoretical framework

To examine the abovementioned objectives, this article extends and adapts the existing Unified Theory of Acceptance and Use of Technology (UTAUT) to the context of implementing an integrated EHR in a hospital setting [9, 13]. Following Holden and Karsh [14], who emphasized the importance of contextualizing the Technology Acceptance Model (TAM) in order to improve its predictive and explanatory power, a contextualized UTAUT is necessary to analyze EHR acceptance in this context [15]. Based on an extensive literature review and workshops, the UTAUT constructs and indicators were adapted to the context of this research. The hypothesized model, shown in Figure 1, builds upon the four original UTAUT constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence

(SI), and Facilitating Conditions (FC). Contrary to the original UTAUT model, these constructs are determinants of attitude towards the EHR (ATT) instead of behavioral intention. As pointed out in prior technology acceptance research, behavioral intention is not suited as the dependent variable when use of the technology is mandatory since attitudes might not align with intentions and actual behavior [16, 17]. The indicators used to measure the latent constructs and the corresponding sources are shown in Table 1.

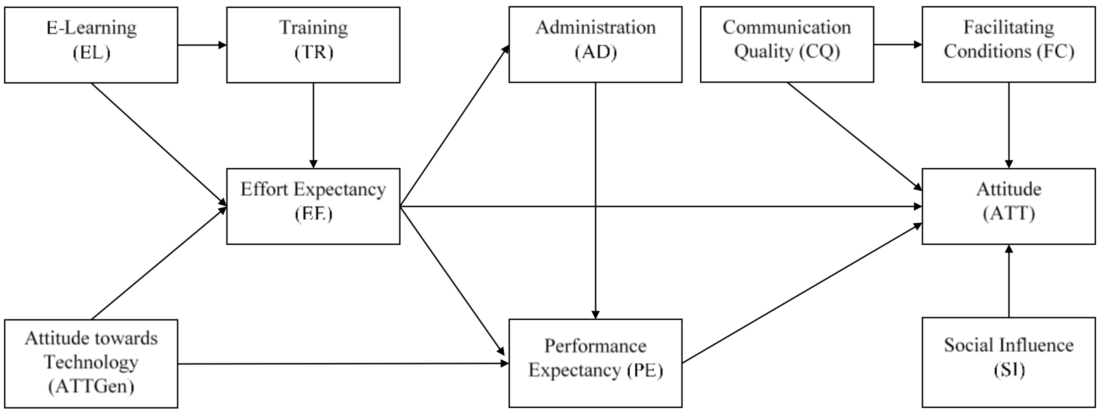

Figure 1: Hypothesized Research Model

Variables	Indicators	Literature
Performance Expectancy (PE)		
	I would find the system useful in my job	[13, 18]
	Using the system increases my productivity	[13, 18]
	Use of the system increases the quality of care provided during my interventions	[3, 8, 19-21]
	Using the system strongly improves patient safety	[19]
Effort Expectancy (EE)		
	I would find the system easy to use	[13, 18]
	Learning to operate the system would be easy for me	[13, 22]
	It would be easy for me to become skillful at using the system	[13, 18]
	My interaction with the system would be clear and understandable	[13, 18]
Administration (AD)		
	Using the system allows me to accomplish administrative tasks more quickly	[13, 22]
	Using the system causes less administrative errors	[20]
	Using the system allows me to do more patient-centered work than before the implementation of the system	[3]

	Overall, I believe that the system helps me to be more efficient in my administrative activities	*Addition based on workshops*
Social Influence (SI)		
	~~People who influence my behavior think that I should use the system~~	[13, 23]
	People who are important to me think that I should use the system	[13, 23]
	The senior management of this hospital has been helpful in the use of the system	[13, 24]
	~~In general, the hospital supports the use of the system~~	[13, 24]
Facilitating Conditions (FC)		
	I have the resources necessary to use the system	[13, 23]
	I have the knowledge necessary to use the system	[13, 23]
	~~The system is not compatible with other systems I use~~	[13, 23]
	A specific person or group is available for assistance with system difficulties	[13, 24]
Training (TR)		
	The training I received before system usage was complete	[25]
	The training I received before system usage gave me confidence in the system	[25]
	The training I received before system usage was adapted to my work context	*Addition based on workshops*
	My level of understanding was substantially improved after going through the training program	[25]
	Overall, the training I received was sufficient	[26]
e-Learning (EL)		
	The e-learning I received before system usage was complete	[25]
	The e-learning I received before system usage gave me confidence in the system	[25]
	The e-learning I received before system usage was adapted to my work context	*Addition based on workshops*
	My level of understanding was substantially improved after going through the e-learning program	[25]
	Overall, the e-learning I received was sufficient	[26]
Communication Quality (CQ)		
	I have received information regarding the use of the system in a timely manner	[20]
	I am satisfied with my involvement in the decision process regarding the new system	*Based on* [5]
	The management of the hospital was transparent in their decision making regarding the new system	*Addition based on workshops*
	Overall, the information I received regarding the system was satisfactory	*Addition based on workshops*
Attitude toward the System (ATT)		
	Using the system is beneficial for me	[18]
	Using the system is a good/bad idea	[18]
	Working with the system is fun	[18]
Attitude toward Technology (ATTGen)		
	IT is a necessary tool in my work context	*Adapted from* [27]
	Using IT is a good/bad idea	*Adapted from* [18]
	I like experimenting with new IT	[3]
	Overall, I like working with technology	*Adapted from* [18]

Table 1: Latent constructs and measurement indicators

Note: stricken through indicators were removed during measurement model evaluation (see Appendix A)

In addition to the contextualized UTAUT variables, this article extends the model using five additional constructs. First, as a fundamental characteristic of integrated EHRs, administrative simplification and gains in administrative process efficiency are crucial aspects to achieve a successful EHR implementation [5, 28]. Therefore, we extend the UTAUT model by adding an administration (AD) construct as we hypothesize that the individual's perception of the administrative simplification due to the EHR influences the perceived performance of the EHR. Contrary to the existing body of healthcare technology acceptance research, which mainly interprets PE as the expected performance related to healthcare or a mix of administrative efficiency and healthcare, this article separates the two concepts by taking into account the performance in terms of administrative efficiency using a separate construct in the model. This is the first study examining the unique role of administrative simplification in the acceptance of an EHR.

Second, throughout the years, scholars demonstrated the importance of the quality of communication to staff when implementing new technologies [5, 20]. To date, however, this aspect is underexplored in technology acceptance research. This article therefore incorporates a 'communication quality' (CQ) variable in the model, which focuses on the communication hospital staff received regarding the implementation and use of the EHR and management decision making. A third important dimension is the attitude towards information technology in general (ATTGen). As multiple studies have already shown, the perception towards information technology in general plays an important part in explaining the acceptance of a specific technology. The more positive an individual perceives technology in daily life, the more likely this individual will also perceive technology in the workplace in a positive way [12, 29]. The final two additions to the research model are related to the training courses hospital staff received before EHR use. Hospital staff members had to complete an e-learning course, which contained the basic features of the EHR, after which they had to follow a hands-on training course in a classroom with individual exercises. Based on the work of previous scholars, we hypothesize the way in which hospital staff perceived the training courses to significantly affect the extent to which health professionals perceive the EHR as easy to use [26, 30, 31]. Therefore, an e-learning (EL) variable was added for the e-learning module and a training (TR) variable for the classroom training.

Besides testing the hypothesized model in the context of implementing a hospital EHR, a second contribution of this article to the literature is to test whether the importance of the constructs in predicting and explaining EHR acceptance varies over time. To date, limited evidence on the effect of the implementation stage on technology acceptance is available, especially in the context of healthcare, as the vast majority of research is cross-sectional and the existing longitudinal research, while it does contain indications for differences in path coefficients over time, mostly fails to test whether these differences are significant [9, 14, 32-34]. If significant differences do arise over time, this would mean hospital management and EHR providers have to adjust their policy according to the implementation stage as different factors are important to achieve EHR acceptance.

2. Methods

2.1 Setting and design

The research was conducted in a Belgian hospital which was planning to implement an integrated EHR in 2018 to reach EMRAM[1] adoption stage 6 or 7 using a "big bang" implementation strategy. The hospital employs roughly 3,000 staff members and accounts for more than 650,000 patient consultations each year. Following the limited longitudinal literature on the topic, we opted for three measurements in time. As hospital staff needs a first impression of the new EHR, the first measurement took place one month before the implementation after which hospital staff had completed the training program. The second measurement was conducted 11 months after the implementation to give hospital staff the chance to familiarize themselves with the new system and work protocols. The final measurement, performed 19 months after the implementation, mainly served as a control measurement to check whether sufficient measurements were conducted to conclude on the evolution of the acceptance behavior over time.

2.2 Survey development, content and distribution

To test the proposed model, it was converted into an online questionnaire. The model, and subsequently the questionnaire, were developed using the theoretical and empirical insights from previous technology acceptance research and workshops with hospital management and staff. The survey consisted of two main sections. First, hospital staff's EHR perceptions were measured using the indicators previously shown in Table 1. Each indicator was measured using a 7-point Likert scale ranging from "Strongly disagree" to "Strongly agree" and in the wording of the indicators the word 'system' was replaced by the name of the EHR. In the second section, socio-demographic and professional characteristics were

[1] The Electronic Medical Record Adoption Model (EMRAM)

gathered. Other than the tense used in the formulation of the indicators, the survey instrument was identical across the three measurements.

To translate the original indicators to Dutch and adjust them to cross-cultural differences, this article employed the combined translation technique of Cha et al. [35]. After survey translation, multiple workshops with the hospital management and a representative group of hospital staff members were organized to assess the relevance and clarity of the survey instrument. Prior to the distribution of the survey, a final pre-test was conducted among ten health professionals after which the survey was evaluated and approved by two independent ethical committees. The survey was distributed using the e-mail system of the hospital to all health professionals, ranging from medical secretaries to nurses. The first measurement gathered 405 responses, the second measurement 812 responses, and the final measurement 304 responses, corresponding to a response rate of 14%, 28%, and 11% respectively. These sample sizes are well above the required sample sizes for the analyses to achieve a statistical power of 80% for the hypothesized model [36, 37]. As shown in Table 2, the demographic and professional characteristics of the three samples are highly comparable, meaning potential differences over time are not attributable to different samples.

Respondent characteristics		Frequency (%)		
		T1	T2	T3
Gender	Male	16.97	25.25	23.03
	Female	83.21	74.75	76.97
Age	Under 26	10.62	7.14	5.26
	26-35	29.88	24.75	24.01
	36-45	25.93	28.33	24.67
	46-55	22.22	26.48	26.97
	Above 55	11.36	13.30	19.08
Profession	Physician	5.43	17.24	11.18
	Nurse	75.31	63.05	62.50
	Administrative	4.69	4.31	5.26
	Other	14.57	15.39	21.05
Years of experience	Under 1	6.42	6.90	4.61
	1-10	44.94	38.30	28.29
	10-20	23.46	25.00	26.97
	20-30	15.06	18.47	22.04
	Above 30	10.12	11.33	18.09
Respondents		405	812	304

Table 2: Respondent characteristics

2.3 Data analysis

The structural and measurement models are estimated using partial least squares structural equation modelling (PLS-SEM), an exploratory multivariate data analysis technique designed by Hold [38] and recently employed by multiple scholars in the research field [10, 12, 36, 39-42]. The evaluation of the measurement models is discussed in detail in Appendix A. Before testing the significance of the hypothesized relations in the models, the structural models were first checked for collinearity issues. With VIFs on the construct level ranging from 1 to 3.121, no collinearity issues bias the results. Furthermore, the structural models are assessed by examining coefficients of determination, significance of the path models, and effect sizes. The abovementioned analyses were performed for each of the three models (T_1, T_2, and T_3) separately as full measurement invariance should be established before pooling the data [36].

To examine whether there are significant evolutions in the path coefficients between the three different time points, this article employs partial least squares multigroup analyses

(PLS-MGA) and permutation tests. Before employing these techniques, measurement invariance is examined since at least partial measurement invariance should be achieved before comparing multiple groups [43, 44]. We checked the partial measurement invariance criteria using the MICOM[2] procedure of Henseler et al. [43, 45]. Configural invariance is established for all latent constructs. Compositional invariance, and thus partial measurement invariance, could however not be established for FC and SI (T_1 versus T_2); AD, FC, and SI (T_1 versus T_3); and AD (T_1 versus T_2). The analyses were performed using the SmartPLS software [46]. We applied the path weighting scheme and used the bias-corrected confidence intervals to evaluate the significance of parameter estimates and p values to assess significant differences in the multigroup analyses, both resulting from the bias-corrected bootstrapping procedure with 10,000 subsamples [47]. We employed the Šidák procedure to solve the alpha inflation problem as this resulted in a lower p value than the Bonferroni correction.

[2] Measurement Invariance of Composite Models (MICOM).

3. Results

3.1. Structural models

The results of the PLS-SEM algorithm and bootstrapping procedures are shown in Table 3. The results show consistent significant positive coefficients for most of the hypothesized relations, except between attitude towards technology (ATTGen) and performance expectancy (PE) (T_3), facilitating conditions (FC) and attitude towards the EHR (ATT) (T_1, T_2, T_3), and social influence (SI) and ATT (T_2,T_3)[3]. The consistent insignificant effect of FC is remarkable, which indicates that the support, resources, and knowledge of hospital staff do not impact their EHR attitudes. Throughout the three measurements, effort expectancy (EE) and performance expectancy (PE) are clearly among the largest determinants of ATT. Furthermore, while EE is the latent variable with the largest effect on ATT before system implementation, PE becomes the variable with the largest effect on ATT once the system was implemented.

Structural model	T1				T2				T3			
Path	ß	Effect size f^2	ß confidence interval[a]		ß	Effect size f^2	ß confidence interval[a]		ß	Effect size f^2	ß confidence interval[a]	
			2.5%	97.5%			2.5%	97.5%			2.5%	97.5%
AD → PE	0.573*	0.514	0.479	0.653	0.696*	1.287	0.649	0.737	0.648*	1.056	0.566	0.720
ATTGen → EE	0.389*	0.239	0.300	0.473	0.189*	0.057	0.137	0.241	0.227*	0.077	0.128	0.323
ATTGen → PE	0.113*	0.030	0.038	0.189	0.047*	0.011	0.015	0.082	0.046	0.009	-0.015	0.107
CQ → ATT	0.124*	0.026	0.040	0.210	0.113*	0.026	0.060	0.161	0.186*	0.073	0.099	0.277
CQ → FC	0.663*	0.784	0.596	0.711	0.656*	0.755	0.606	0.696	0.608*	0.587	0.507	0.680
EE → AD	0.708*	1.003	0.646	0.756	0.702*	0.972	0.661	0.736	0.681*	0.863	0.596	0.743
EE → ATT	0.404*	0.213	0.306	0.506	0.210*	0.077	0.148	0.271	0.141*	0.032	0.046	0.245
EE → PE	0.247*	0.083	0.155	0.344	0.246*	0.156	0.196	0.298	0.294*	0.199	0.210	0.386
EL → EE	0.144*	0.020	0.023	0.257	0.271*	0.057	0.184	0.356	0.155*	0.018	0.026	0.273
EL → TR	0.649*	0.727	0.569	0.703	0.728*	1.128	0.682	0.763	0.715*	1.047	0.615	0.774
FC → ATT	0.003	0.000	-0.090	0.087	-0.002	0.000	-0.047	0.047	-0.023	0.001	-0.098	0.053
PE → ATT	0.384*	0.223	0.285	0.481	0.624*	0.713	0.567	0.679	0.638*	0.822	0.555	0.713
SI → ATT	0.072*	0.013	0.004	0.139	0.038	0.004	-0.008	0.083	0.053	0.007	-0.023	0.127
TR → EE	0.315*	0.098	0.210	0.412	0.341*	0.090	0.255	0.422	0.389*	0.115	0.260	0.512

Table 3: Structural model

[a] Bias-corrected confidence interval based on 10,000 bootstrap samples.
*Significant at significance level p<0.05

[3] Significance level p<0.05.

The additions of this study to the original UTAUT model perform notably well as all added relations, except for ATTGen-PE at T_3, are significant. The importance of taking into account the administration (AD) construct is clearly reflected in the results as both relations (EE-AD and AD-PE) are highly significant over the three measurements. Furthermore, the training hospital staff received impacts EE substantially. Unsurprisingly, the classroom training (TR) has a larger effect on EE than the e-learning (EL) as it is hands-on training specifically adapted to the work context in comparison to a more general basic online course. Moreover, the perception of the e-learning significantly impacts the perception of the classroom training. The other implementation context variable, communication quality (CQ), has a significant effect on ATT and FC. CQ is even the second largest determinant of ATT in the final measurement. Finally, ATTGen consistently has a larger effect on EE than on PE.

	T1		T2		T3	
Latent constructs	R^2	R^2 adjusted	R^2	R^2 adjusted	R^2	R^2 adjusted
Training (TR)	0.421*	0.420*	0.530**	0.530**	0.511**	0.510**
Effort Expectancy (EE)	0.422*	0.418*	0.398*	0.396*	0.366*	0.360*
Performance Expectancy (PE)	0.681**	0.679**	0.809***	0.809***	0.788***	0.786***
Administration (AD)	0.501**	0.500**	0.493*	0.492*	0.463*	0.461*
Facilitating Conditions (FC)	0.440*	0.438*	0.430*	0.429*	0.370*	0.368*
Attitude (ATT)	0.697**	0.694**	0.789***	0.788***	0.803***	0.800***

Table 4: Coefficient of determination

Magnitude of variance explained: ***substantial, **moderate, *weak

As shown in Table 4, the hypothesized model is able to explain between 69% and 80% of the variance in ATT. Remarkably, the performance of the model in terms of explaining ATT improves over time, which indicates the model is more suited to explain than to predict EHR acceptance. Furthermore, by adding AD and ATTGen to EE as determinants of PE, we are able to explain a substantial amount (68%-81%) of the variance in PE.

3.2. Multigroup analyses

To examine whether significant differences in path coefficients exist between the three measurements, we used three pairwise PLS-MGA [44, 48, 49]. As shown in Table 5, the results show that two path coefficients significantly increased between the measurement before EHR implementation and the first measurement after EHR implementation. First, the path coefficient of AD-PE increased significantly by 0.122, which means the effect of administrative simplification on performance expectancy becomes more important over time. Second, the coefficient of the PE-ATT relationship also increased, meaning PE becomes more important in explaining staffs' attitudes towards the EHR. While the latter difference persists and intensifies on the longer run (T_1 versus T_3), the first effect does not as it is partially offset by a small decrease between T_2 and T_3 rendering the long term increase no longer significant.

	T1 vs T2		**T1 vs T3**		**T2 vs T3**	
	ß$_1$ – ß$_2$	p value	ß$_1$ – ß$_3$	p value	ß$_2$ – ß$_3$	p value
AD → PE	**-0.122****	0.01	~~-0.074~~	~~0.205~~	~~0.048~~	~~0.289~~
ATTGen → EE	**0.200****	<0.001	**0.162***	0.015	-0.038	0.499
ATTGen → PE	0.065	0.114	0.067	0.171	0.002	0.949
CQ → ATT	0.011	0.843	-0.062	0.330	-0.073	0.174
CQ → FC	~~0.007~~	~~0.834~~	~~0.055~~	~~0.281~~	0.048	0.323
EE → AD	0.006	0.859	~~0.027~~	~~0.568~~	~~0.021~~	~~0.625~~
EE → ATT	**0.194****	0.001	**0.263****	<0.001	0.070	0.248
EE → PE	0.000	0.990	-0.048	0.469	-0.048	0.362
EL → EE	-0.127	0.080	-0.011	0.904	0.116	0.134
EL → TR	-0.079*	0.036	-0.066	0.189	0.013	0.780
FC → ATT	0.005	0.915	~~0.026~~	~~0.667~~	0.021	0.654
PE → ATT	**-0.240****	<0.001	**-0.254****	<0.001	-0.014	0.778
SI → ATT	0.034	0.417	~~0.019~~	~~0.724~~	-0.015	0.728
TR → EE	-0.027	0.695	-0.074	0.371	-0.047	0.539

Table 5: Multigroup analyses

** p<0.01, * p<0.05, **p<0.0167% (Šidák correction)**

Note: stricken through numbers cannot be interpreted due to the lack of partial measurement invariance

Furthermore, Table 5 shows two significant decreases in path coefficients. First, the path coefficient of ATTGen-EE decreases significantly between T_1 and T_2/T_3. This means that, as hospital staff gains more experience using the EHR, prior experiences with technology in general play a less important role in the extent to which the EHR is found easy to use. Second, the effect of EE on ATT also decreases significantly over time, which means the ease of use of the EHR becomes less important in explaining EHR attitudes as hospital staff gains more experience using the system. While the magnitude of the difference of the latter intensifies further when comparing T_1 to T_3, the magnitude of the first decreases slightly. The abovementioned analyses were repeated using permutation tests, which lead to comparable results and identical conclusions[4].

[4] As permutation tests are sensitive to sample size and the sample size at T_2 is more than double the sample sizes of the other measurements, the permutation analyses were repeated 10 times each using a different random subsample of T_2. The results are available upon request.

4. Implications

The results of this study, while being based on only one hospital and not having access to panel data, have important implications for both scholars and practice as the results highlight on which factors to focus in which EHR implementation stage. First, the administrative simplification (AD) construct outperforms both the additions and core UTAUT constructs. This clearly demonstrates the importance of focusing on the administrative simplification due to the EHR as this influences the usefulness of the system substantially. This study is the first to take the unique role of administrative simplification into account when examining IT acceptance. While we expect AD to play a more pronounced role in jobs where administration is not the core business, like healthcare, future research should be aimed at exploring the role of AD in other contexts and technologies.

Second, the results demonstrate the important roles of effort and performance expectancy (EE and PE) in explaining attitude towards the EHR. This is somewhat surprising for EE as the research field has so far found mixed results on its importance and significance [8, 10, 50]. Moreover, a trade-off from effort expectancy (EE) to performance expectancy (PE) is detected with ease of use being the most important factor to focus on before EHR implementation, while performance of the EHR only becomes more important once the system is implemented. This is also a significant contribution to the existing literature as the limited longitudinal literature has so far found mixed results on the effect of EE as users gain more experience using the system and has not yet examined changes in PE over time [13, 51]. These findings thus advocate for conducting more analyses of change over time in future research.

Third, the results highlight the importance of an adequate preparation of the implementation process in achieving EHR acceptance and incorporating these factors in technology acceptance research. More explicitly, hospitals should thus spend significant effort on their communication quality and training hospital staff.

Finally, one factor to achieve EHR acceptance is somewhat out of the reach of hospital management as it is more individually determined. Prior experiences with IT (ATTGen) have a substantial impact on the extent that staff finds the EHR easy to use and its performance in the first stages of the implementation process. On the longer run, however, ATTGen is no longer an important enabler or barrier to EHR acceptance, which explains the insignificant effect in the final measurement. Furthermore, two additional relations in the model were not proven to impact EHR acceptance. First, the insignificant effect of social influence can be explained by the mandated use of the EHR. Second, the insignificant role of facilitating conditions in this context is a surprising finding and provides an avenue for further research.

5. Conclusion

This study adds to the existing body of healthcare technology acceptance research by formulating a model for the context of integrated hospital EHRs. First, we find evidence for the important role administrative simplification plays in the acceptance of an EHR. Furthermore, the analyses show a specific set of implementation factors (i.e. communication quality and training) to significantly affect the acceptance of an EHR. Finally, we show prior IT experiences mainly influence the extent to which the EHR is easy to use and to a lesser extent its performance, and is mostly important in the first stages of the implementation process.

Second, by employing a repeated cross-sectional design and multigroup analyses to test for evolutions in the path coefficients over time, we found evidence for a trade-off between effort expectancy (EE) and performance expectancy (PE) in explaining ATT. While the effect of PE on ATT increases significantly over time, the effect of EE decreases substantially and is thus mainly an important factor before implementation of the EHR. In future research, scholars should thus opt for analyses of change over time, ideally using longitudinal data, to fully explore and understand the acceptance of a technology as the implementation stage significantly affects the importance of the different constructs in explaining the acceptance of the EHR. The findings of this research provide a valuable guide to hospital management and healthcare technology developers by empirically showing on which aspects to focus during the different stages of the implementation trajectory of an EHR.

Contributions to the literature

What was already known on the topic?

- Integrated hospital Electronic Health Record (EHR) systems, when implemented successfully, have the potential to improve quality of care, efficiency, and patient safety.
- Technology acceptance models are suited to examine technology in healthcare, including EHRs.
- Most of the studies fail to take into account the quality of communication, training, the impact of the EHR on administration, and prior experiences with technology.
- A major caveat in the literature is the dominant use of cross-sectional research designs and lack of analyses of change over time.

What this study added to the body of knowledge?

- This study developed and tested a model to examine the acceptance of an integrated EHR system in a hospital setting by extending and adapting the existing UTAUT model.
- This study highlights the importance of including the extent to which the EHR leads to administrative simplification, communication quality, training, and attitude towards technology in general to fully understand EHR acceptance.
- Finding significant evolutions in path coefficients over time, this study shows hospital management and healthcare technology suppliers should adjust their implementation policy depending on the implementation stage.

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Author contributions

All the authors contributed equally.

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