The Influence of Relational Intellectual Capital and Information Technology on Hospital Efficiency

Andrzej Chluski
Czestochowa University of Technology, Poland
andrzej.chluski@pcz.pl

Abstract: Knowledge management and building intellectual capital are essential for effectively operating healthcare entities. Modern information and communication technologies have an increasing impact on the activities of healthcare entities, which is attributable to the relationship of ICT and purely medical technologies with the use of ICT in knowledge and intellectual capital management. Proper management of the areas of hospital activity mentioned above significantly impacts its effectiveness and efficiency. This paper aims to present and verify a model for determining the impact of the level of relational intellectual capital and the degree of maturity of information and communication technology on the quality and effectiveness of medical services provided by hospitals in Poland. The research model was created using structural equation modelling (SEM). The basic structural model consists of four constructs corresponding to the phenomena studied and the relationships between these constructs. Each construct, as a latent variable, has its measurement model. The measurement models use a survey conducted among the management staff of Polish hospitals. The questionnaires contain carefully selected questions that are indicators of SEM measurement models. The estimation of the model parameters and accuracy was assessed using the partial least squares structural equation modelling (SEM-PLS) methodology. The hypotheses proposed in the paper were verified positively. The model meets the required quality criteria, and all parameters are statistically significant. The level of relational intellectual capital and the degree of maturity of information and communication technology positively and significantly impact the quality and effectiveness of medical services provided in hospitals. The research findings may be helpful for hospital management at the strategic management level.

Keywords: Healthcare management, Information and communication technology, Knowledge management in healthcare, Relational intellectual capital, SEM-PLS modelling

1. Introduction

Modern information and communication technologies (ICT) are widely used and affect almost all aspects of human activity. Despite many years of dynamic development, medical entities are unlikely to take the lead in the development of IT, except for advanced and innovative medical technologies that rely heavily on computer-based methods. The pace of development of medical technologies and implementation of new treatment methods is much slower due to factors such as lengthy and costly clinical trials or complicated approval procedures for new technologies and treatments. As a result, hospital managers need to work closely with IT managers and create and implement a development strategy that considers the medical sector's peculiarities and changing IT trends and requirements. This collaboration will make it possible to exploit the potential of medical IT, improve the efficiency of operations and the quality of services provided, and increase the competitiveness of medical facilities in the market.

Economic efficiency is an essential aspect of managing both commercial and public hospitals. Many healthcare systems around the world fund the activities of medical entities, ranging from private to state-funded systems. Despite differences in pricing and financing of medical services, hospital performance management is based on similar principles. Measures of financial efficiency, such as classic ratios, can be used in any system and can even be adapted to the unique conditions of the activities of hospitals. Effective hospital performance management is critical to providing quality medical services to patients.

The knowledge and skills of hospital employees represent critical intangible intellectual capital. It is a particular resource from a management perspective because the organisation does not own it. It cannot be assumed that a business organisation is the owner of the knowledge of its employees because, at best, it can only be considered a leased resource.

In addition to the knowledge and experience of staff, hospitals have intangible assets that can affect their overall performance and success. Such assets include the hospital's reputation, the general perception of its quality and reliability, and patients' opinions about their experiences with its services, staff, and facilities. The hospital's reputation is improved through consistent action, positive opinions, and effective communication with patients and their families. It is often based on factors such as the quality of medical care, patient treatment outcomes, availability of advanced treatment methods and technologies, and the hospital's commitment to patient satisfaction.

Likewise, relational intellectual capital is of great importance in hospital activities. It refers to the hospital's relationship with patients, their families, and other stakeholders. Relational capital is formed by a hospital's reputation, brand image, and trust patients and their families place in the hospital. It is critical to its success, enabling an organisation to build long-term relationships with patients and stakeholders and become a trusted service provider.

The paper describes a research model created and tested using partial least squares structural equation modelling (PLS-SEM). Rigdon (2013) argued that PLS is a widely used method for testing and validating scientific theories. Multiple simulations have demonstrated that PLS effectively tests hypotheses in various research model configurations.

2. Background and Literature Review

The level of the development of relational intellectual capital (RIC) in healthcare refers to the extent to which healthcare organisations can leverage their relationships with employees, patients, and other stakeholders to create and share knowledge and improve outcomes (De Leaniz, Del Bosque, 2013).

Developing RICs in healthcare is critical to improving healthcare outcomes and patient satisfaction. Habersam and Piber (2003) examined the relationship between RIC and patient satisfaction in European hospitals and showed a positive effect of RIC. Other studies have looked at the impact of RICs on healthcare innovation. Chang, Wu and Shei (2014) examined the impact of RICs on innovation in Taiwanese healthcare. The study found that RIC is positively linked to the implementation of healthcare innovations.

Of great importance for the effective development of RIC is the patients' perceived quality and effectiveness of treatment procedures (Lardo et al. 2017). Furthermore, Lenart (2015) showed that maintaining good relations with customers and partners is a prerequisite for good organisational governance.

The development of RIC in healthcare can also lead to improved organisational performance. A study by Wu and Hu (2012) confirmed the strong impact of RIC on hospital organisational performance. These researchers found that RIC positively impacts organisational performance by facilitating communication and collaboration between healthcare professionals, improving efficiency and effectiveness in providing healthcare services.

The problems of acquiring knowledge of medical personnel were studied by Wielki, Jurczyk-Bunkowska, and Madera (2020). Based on their findings, the authors confirmed that properly aligned information technology positively impacts organisational efficiency.

Modern ICTs support hospital information systems, which are typically associated with several core areas of activity, such as a patient's stay and medical data related to this stay, healthcare delivery, administration, and other support activities (Chluski, 2018) (Golinelli et all, 2020) (Turulja, 2020).

The maturity of information and communications technology in healthcare refers to the sophistication of the technology-based tools and systems used in the healthcare sector. The maturity of ICTs in healthcare can be assessed based on various factors such as the availability of electronic health records (EHRs), telemedicine capabilities, health analytics, and mHealth apps (Carvalho, Rocha, Abreu, 2016) (Burmann, Meister, 2021).

Public funds mainly finance health services (e.g., large insurance companies or state budgets). Therefore, in most countries, healthcare entities operate in a regulated and restricted market. For this reason, employing ICTs that have been used and proven in other areas of the economy is critical. This avoids errors and helps adapt ICTs to the specifics of the healthcare sector (Feldman S., Buchalter, Hayes, 2018).

The efficiency and effectiveness of healthcare are of interest to scientists, managers, politicians, and other social organisations. Legal regulation, actions of politicians and scientists, and practical actions of managers in this area vary depending on the degree of economic development of individual countries and the type of healthcare financing system. Evaluation of the efficiency of hospital operations should consider a country's specificity (Kozun-Cieślak, 2020)(Cantor, Poh, 2018).

The efficiency of the operation of public hospitals is a complex problem. Even in the case of commercial entities, profit generation is only one of the primary goals of their operations. In addition to providing medical services, hospitals pursue several social goals, e.g., saving patients' lives, preventing and improving public health, or promoting healthy lifestyles (Pirozzi, Ferulano, 2016).

The positive impact of IT support on building human capital and the performance of Polish hospitals was presented by A. Chluski (2018). The present paper aims to complement that research.

Jameton and McGuire (2002) examined more broadly the concept of healthcare quality in the area of the quality of the healthcare services themselves (substantive dimension), in the area of patient experiences and patient perceptions of healthcare quality (social dimension), in the area of controlling costs (economic size), and the area of environmental impact. Olkiewicz and Bober (2015) discuss the role of quality in the healthcare service provision process in Polish hospitals. Krukowska-Miler (2017) demonstrated that patients seek understanding, interest, and partnership in physicians, which are soft skills that can be considered relational capital.

Habersam and Piber (2003) believe that hospitals, primarily public organisations, must be competitive while maintaining high efficiency, responsibility, transparency, and quality of services.

3. Hypotheses and Research Model

The theoretical constructs proposed below, along with the relationships between each other, form the research model presented in this paper.

Construct: the efficiency of providing medical services is identified in three dimensions. The first concerns the financial indicators of the hospital's performance, such as profit, liquidity, and repayment of financial and tax liabilities. The second is related to the perception of hospital development by managers. The third dimension deals with the staff's views on the economic development of the hospital (Cylus et al., 2016) (Cylus, Smith, 2020).

Construct: the degree of maturity of information and communication technology is identified based on the managers' opinions on the degree of use and usability of professional and specialised computer systems in both the administrative and medical parts of the hospital departments (Carvalho et al., 2019) (Gomes, Romão, 2018),

Construct: the level of development of relational intellectual capital refers to the degree of development of intangible assets that affect the relationships between the hospital, patients, and other stakeholders. The most important resources of this type are the hospital's reputation, good experiences and loyalty of patients, the reputation of individual employees, conditions and perceived quality of treatment, specialisation, and scope of medical activities of the hospital (Wong, 2019) (Chatterji, Kiran, 2017).

Construct: the quality of provided services refers to evaluating the quality of health care in various areas, such as diagnosis, treatment, and rehabilitation. It also concerns assessing the availability of services and barriers that make it difficult or impossible for patients to receive medical care, such as the lack of medical personnel, the long waiting time for appointments, and the cost of treatment (Mosadeghrad, 2012) (Upadhyai, 2019).

In the SEM methodology, the primary research model is the structural model. It is formed by theoretical constructs and the relationships that exist between each other. The constructs correspond to latent variables. Indicators are used to measure these variables. The indicators with their corresponding latent variables form measurement models. The indicators are quantitatively measured indicators, mainly utilising the interval Likert scale.

The research hypotheses are related to the relationship between the theoretical constructs. The SEM-PLS model based on path analysis allows for the verification of the hypotheses presented in the paper. It is possible to determine the fundamental relationships between latent variables in numerical form, their statistical significance, and the direction of effect.

The following research hypotheses were posed as follows:

> *H1. The level of development of relational intellectual capital positively affects the efficiency of providing medical services.*
>
> *H2. The level of development of relational intellectual capital positively affects the quality and availability of medical services.*
>
> *H3. The maturity of information and communication technologies positively affects the efficiency of providing medical services.*
>
> *H4. The maturity of information and communication technologies positively affects the quality and availability of medical services.*

Table 1: Constructs, Latent Variables, and Indicators for Measuring These Variables

Theoretical construct	Latent variable	Measuring model indicator
Level of Relational Intellectual Capital development	Relat	Relat-1
		Relat-2
		Relat-3
Maturity of Information and Communication Technologies	ITmat	ITmat-1
		ITmat-2
		ITmat-3
The efficiency of Providing Medical Services	Effi	Effi-1
		Effi-2
		Effi-3
Quality and Availability of Medical Services Provided	Qual	Qual-1
		Qual-2

Figure 1 shows the research model, which includes a structural model (represented by latent variables in ovals) and four measurement models (external models) for each latent variable. The arrows in the diagram correspond to the relationships between the latent variables in the structural model. The arrows in the measurement models represent the relationships between the latent variables and the corresponding indicators. The calculation results for this model are shown in Figure 1.

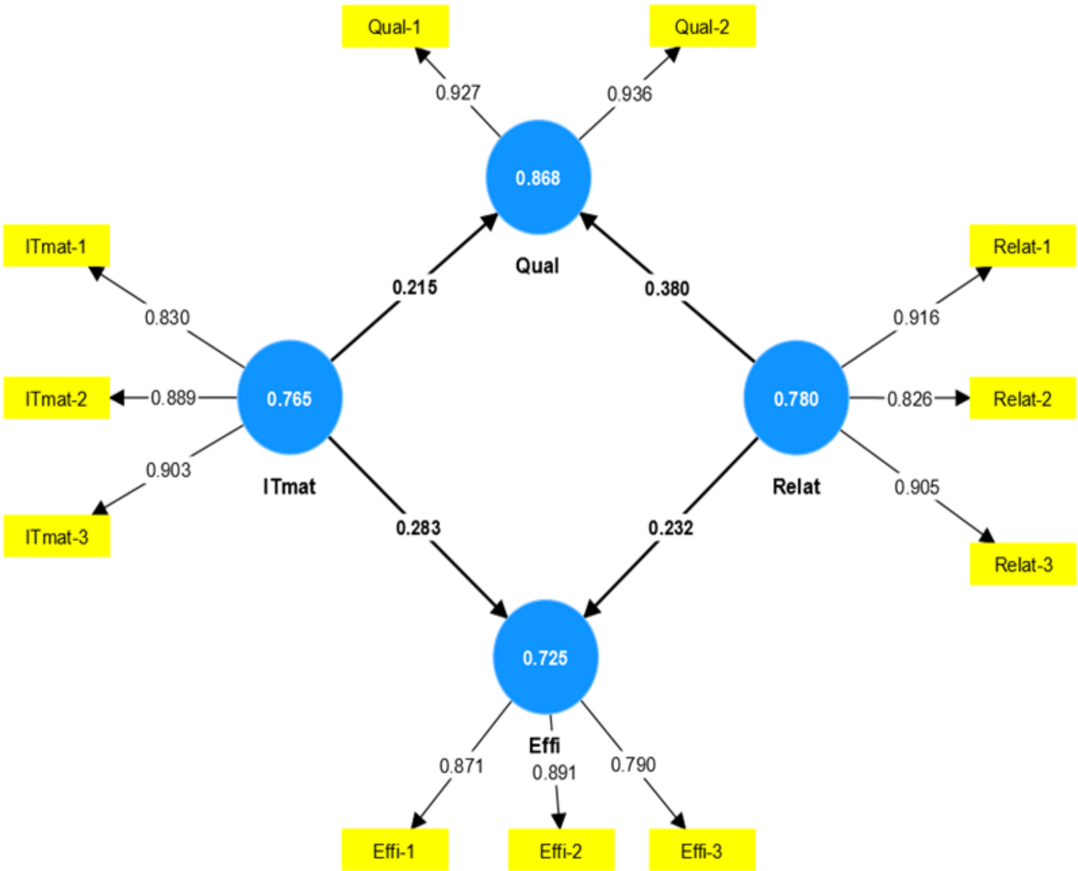

Figure 1: Structural SEM-PLS research model

4. Research Sample and Methodology

Structural equation modelling (SEM) tests hypothesised relationships between observable and non-observable variables. This applies to non-experimental correlation studies, which use passive observation as a research method. The partial least square structural equation modelling (PLS-SEM) method was used for the calculations. Goodhue, Lewis, and Thompson (2012) emphasised that, as with other techniques, there is an increase in standard deviation and a decrease in statistical power when using PLS-SEM with small samples. Nevertheless, this method proves more reliable when the data distribution deviates moderately from the normal distribution. Bootstrapping resampling can be used to avoid the problems of non-normal data distribution and small research samples.

For the measurement of observable variables, a questionnaire was created with sentences (statements) corresponding to the indicators of the measurement models in SEM-PLSM. An interval Likert scale was used for this purpose. Questionnaires were sent to selected managers of hospitals in Poland. The distribution of hospital types in the research sample was similar to that of the entire population of Polish hospitals. Hospitals were divided into groups depending on the type of funding body (or owner) (Floyd, Fowler, 2009). Questionnaires were collected from various regions of Poland, and ninety-four correct responses were received. Poland has just over 900 hospitals (Local Data Bank, 2022).

The minimum sample size was estimated with appropriate assumptions about the test's statistical power (Kock, Moqbel, 2016). It was calculated by assuming the smallest path coefficient of 0.210, a significance level of 0.05, and a test power of 0.70.

The research sample was sufficient to yield adequate parameters of the research model for the SEM-PLS methodology. The minimum sample size for the inverse square root method was 84, while for the gamma-exponential method, it was 73 (Kock, Hadaya, 2018). The statistical significance of the results and estimation of standard errors were performed using bootstrapping. Smart-PLS software was used for the calculations.

5. Research results and model evaluation

The structural model in Figure 1 shows the latent variables and their relationships in the form of arrows with corresponding path coefficient values. The values of these coefficients and their statistical parameters are shown in Table 2. All coefficients are statistically significant ($p < 0.05$). The ovals shown in Figure 1 represent individual latent variables. Inside these ovals are average variance extracted (AVE) values for each latent variable. AVE " is a measure of the amount of variance captured by a construct in relation to the amount of variance due to measurement error" (Fornell, Larcker, 1981).

Table 2: Path Coefficients of the Structural Model and Their Statistical Parameters

	Original sample	Sample mean	Standard deviation	T statistics	p-values
ITmat -> Effi	0.284	0.298	0.087	3.255	0.001
ITmat -> Qual	0.209	0.223	0.114	1.829	0.034
Relat -> Effi	0.232	0.237	0.100	2.317	0.010
Relat -> Qual	0.415	0.411	0.118	3.503	0.000

Table 3 shows the outer loadings calculated for the original sample and those computed using bootstrapping: mean, standard deviation, T-statistic, and p-value. The path parameters of the measurement models are statistically significant and greater than 0.75.

Table 3: Path Coefficients of Measurement Models

	Original sample	Sample mean	Standard deviation	T statistics	p-values
Effi-1 <- Effi	0.870	0.860	0.067	12.974	0.000
Effi-2 <- Effi	0.891	0.882	0.058	15.406	0.000
Effi-3 <- Effi	0.790	0.789	0.076	10.392	0.000
ITmat-1 <- ITmat	0.834	0.834	0.058	14.339	0.000
ITmat-2 <- ITmat	0.885	0.880	0.043	20.605	0.000
ITmat-3 <- ITmat	0.904	0.898	0.034	26.716	0.000
Qual-1 <- Qual	0.847	0.843	0.054	15.616	0.000

	Original sample	Sample mean	Standard deviation	T statistics	p-values
Qual-2 <- Qual	0.934	0.934	0.023	41.070	0.000
Qual-3 <- Qual	0.839	0.834	0.061	13.805	0.000
Relat-1 <- Relat	0.912	0.913	0.020	45.388	0.000
Relat-2 <- Relat	0.827	0.820	0.073	11.271	0.000
Relat-3 <- Relat	0.907	0.907	0.025	35.856	0.000

The path coefficients of the measurement models presented in Table 3 are expressed in less than one relative form. Based on them, both the path coefficients of the external and external models are statistically significant, positive, and have relatively large values. The table also shows the results of bootstrapping calculations.

5.1 Quality Criteria for the Measurement Model

The SEM-PLS modelling evaluation does not use a single global indicator of model quality. In research practice, several indicators have been used to evaluate the structural and measurement models.

In the case of measurement models, verification of their parameters for model reliability and validity is required. This concerns internal consistency reliability, convergent validity, and discriminant validity for each measurement model. The internal consistency reliability was determined using composite reliability, Cronbach's alpha coefficient, and Dijkstra's rho_a coefficient. The coefficients determining the internal consistency of the research model are contained in Table 4.

Table 4: Basic Reliability Coefficients for Latent Variables

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	The average variance extracted (AVE)
Effi	0.809	0.809	0.888	0.725
ITmat	0.846	0.852	0.907	0.765
Qual	0.848	0.851	0.929	0.868
Relat	0.860	0.888	0.914	0.780

The most commonly used measure of the reliability of a measurement scale is Cronbach's alpha coefficient (Garson, 2016). Cronbach's alpha values are greater than 0.8. The rho_a and rho_c coefficients assessing composite reliability are also greater than 0.8, whereas the average variance extracted (AVE) for each external model exceeds a threshold value of 0.7. Based on the bootstrapping estimation, all the coefficients in Table 4 can be considered statistically significant.

Table 5 shows the values of loadings and rotated cross-loadings. Loadings are greater than 0.8 (except for Effi-3) and significantly exceed cross-loadings.

Table 5: Values of Loadings and Cross-Loadings

	Effi	ITmat	Qual	Relat
Effi-1	*0.871*	0.239	0.365	0.305
Effi-2	*0.891*	0.243	0.252	0.228
Effi-3	*0.790*	0.345	0.177	0.194
ITmat-1	0.300	*0.830*	0.188	0.192
ITmat-2	0.258	*0.889*	0.325	0.164
ITmat-3	0.305	*0.903*	0.232	0.146
Qual-1	0.271	0.244	*0.927*	0.388
Qual-2	0.309	0.290	*0.936*	0.397
Relat-1	0.305	0.217	0.412	*0.916*

	Effi	ITmat	Qual	Relat
Relat-2	0.105	0.079	0.355	*0.826*
Relat-3	0.312	0.184	0.347	*0.905*

The Fornell-Larcker criterion was used to assess discriminant validity. Table 6 shows the correlation coefficients between latent variables. The diagonal of the table contains the square roots of AVE. The criterion is met because the values on the diagonal of the table are much larger than individual correlations (Santos, Cirillo, 2021).

Table 6: Correlations Between Latent Variables with AVE Root Values (Fornell-Larcker Criterion)

	Effi	ITmat	Qual	Relat
Effi	0.852			
ITmat	0.328	0.875		
Qual	0.312	0.288	0.932	
Relat	0.286	0.190	0.421	0.883

The following criterion that tests discriminant validity is the heterotrait-monotrait ratio (HTMT). HTML values are placed in Table 7. These coefficients are statistically significant and well below the threshold of 0.9 (Henseler, Ringle, Sarstedt 2015).

Table 7: HTMT Criterion Ratios

	Effi	ITmat	Qual	Relat
Effi				
ITmat	0.394			
Qual	0.375	0.334		
Relat	0.325	0.214	0.492	

5.2 Quality Criteria for the Internal Model

The coefficient of determination R^2 is often used to assess the quality of the SEM-PLS model. It is a statistical measure representing the percentage of the dependent variable's variance explained by the model's independent variables. R-square is a measure of model fit to the data. Table 8 shows the R^2 values for latent dependent variables. Based on bootstrapping calculations, the R^2 coefficients can be considered statistically significant (p-value < 0.01).

Table 8: Coefficients of Determination R^2

	Original sample	Sample mean (M)	Standard deviation	T statistics	p-values
Effi	0.159	0.189	0.067	2.387	0.009
Qual	0.222	0.254	0.082	2.707	0.003

The coefficient of determination (R^2) is considered a good indicator for interpreting effect size due to its slightly lower values than correlation coefficients. The effect size is considered small for $R^2 > 0.02$, medium for $R^2 > 0.13$ and significant for $R^2 > 0.26$ (Cohen, 1992) (Cohen, 1988).

Another measure of model quality is the degree of colinearity of individual pairs of model variables. The total variance inflation factor (VIF) used to estimate this colinearity should be less than 5 (Hair et al., 2022) and according to Kock (2015), even less than 3.3. Table 9 shows collinearity statistics (VIF) for the external model.

Table 9: Colinearity Statistics (VIF) for the External Model

	VIF
Effi-1	2.516
Effi-2	2.775

	VIF
Effi-3	1.398
ITmat-1	1.765
ITmat-2	2.223
ITmat-3	2.489
Qual-1	2.183
Qual-2	2.183
Relat-1	2.471
Relat-2	1.870
Relat-3	2.474

The individual internal model variables' colinearity statistic (VIF) is 1.038.

5.3 Indices of the fit of the Structural Model

Basic indicators of model quality are contained in Table 10.

Table 10: Basic Model Quality Indicators

	Saturated model	Estimated model
SRMR	0.074	0.080
Chi-squared	127.621	130.000
NFI	0.759	0.755

Standardised root mean square residual (SRMR) is the difference between the observed correlation matrix and that implied by the model. It allows for assessing the mean level of the discrepancy between the observed and expected correlations as an absolute measure of model fit. A value of less than 0.10 (or even 0.08, according to Hu and Bentler (1999)) is considered a good fit. Henseler et al. (2015) presented SRMR as a measure of goodness of fit for PLS-SEM that can be used to avoid model misspecification.

The normed fit index (NFI) indicates a good fit if it is greater than 0.8. NFI represents an incremental measure of fit. Its main drawback is that it does not penalise the complexity of the model. The more parameters in the model, the higher (i.e., better) the NFI score. For this reason, this indicator is not recommended for more straightforward and less complex models.

Another criterion of model quality is whether the coefficient d_G (from the original sample) is below the confidence interval after bootstrapping calculations. This is a bootstrapping-based test of the discrepancy between the empirical covariance matrix and the covariance matrix implied by the research model. The use of the d_G coefficient was proposed by Dijkstra and Henseler (2015).

Table 11: Results of the Divergence Test Between the Empirical and Implied Covariance Matrix

d_G	Original sample (O)	Sample mean (M)	95%	99%
Saturated model	0.218	0.213	0.263	0.295
Estimated model	0.224	0.215	0.266	0.299

The d_G values for the research model are below the 0.95 confidence interval. Therefore, the differences between the tested matrices are not statistically significant.

6. Discussion and Conclusion

The present paper confirmed the hypotheses concerning the impact of the level of development of relational intellectual capital (variable: Relat) and maturity of information and communication technologies (variable: ITmat) on the quality (Qual) and efficiency of medical services (Effi) provided by hospitals in Poland.

The path coefficients of the research model were statistically significant, confirming the validity of the relationship between the variables included in the model. Furthermore, both the measurement models and the structural model met the statistical and qualitative assumptions that are commonly required in the social sciences for this type of research methodology. Consequently, the study's results can be considered reliable, providing valuable information on the relationships between the variables in the research model.

During the construction of the model, a path connection corresponding to the relationship of quality (Qual) and efficiency of medical services (Effi) was tested. The path coefficients corresponding to the Effi <-> Qual relationship were minimal and not statistically significant. Therefore, this relationship was not included in the research model. The model did not confirm a direct relationship between the quality of services provided and the efficiency of hospital operations.

The model presented in the paper shows the relationships between the constructs studied. In addition to the numerically expressed relative force, these relationships have a specific sense and direction (arrow in the graphical representation of the model). Some researchers equate this direction with a cause-and-effect relationship (Loehlin, 1987, p.13). However, a prerequisite for this type of relationship is demonstrating that the cause occurred earlier (before the effect), which is impossible in SEM modelling. Table 12 shows the numerical values of the relative relationships between the variables of the structural model.

Table 12: Values of Path Coefficients of the Structural Model Estimated Using Bootstrapping

ITmat ->Effi	0.298
ITmat -> Qual	0.223
Relat -> Effi	0.237
Relat -> Qual	0.411

The exploratory research presented in the paper is pilot in nature. The presented research model can inspire further research on analysing the discussed concepts and phenomena. One potential direction for future investigations is developing a hierarchical structure for the research model. This would require the creation of new theoretical constructs hierarchically linked to each other, allowing a more detailed analysis of the relationships between model elements.

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