Enhancing Clinical Decision Support Through Information Processing Capabilities and Strategic IT Alignment

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Abstract. Hospitals heavily invest in Healthcare IT to improve the efficiency of hospital operations, improve practitioner performance and to enhance patient care. The literature suggests that decision support systems may contribute to these benefits in clinical practice. By building upon the resource-based view of the firm (RBV), we claim that hospitals that invest in a so-called information processing capacity (IPC)—the ability to gather complete patient data and information and enhance clinical processes—will substantially enhance their clinical decision support capability (CDSC). After controlling for common method bias, we use Partial Least Squares SEM to analyze our primary claim. Following the resource and capability-based view of the firm, we test our hypotheses on a cross-sectional data sample of 720 European hospitals. We find that there is a positive association between a hospital's IPC and clinical decision support capability (CDSC). IT alignment moderates this relationship. All included control variables showed nonsignificant results. Extant research has not been able to identify those IT-enabled capabilities that strengthen CDSC in hospital practice. This study contributes to this particular gap in the literature and advances our understanding of how to efficaciously deploy CDSC in clinical practice.

Keywords: Clinical decision support capability · Information processing capability · Health information exchange · Information capability · The resource-based view of the firm (RBV) · Strategic IT alignment · Hospitals

1 Introduction

Recent studies recognized that the adoption and effective use of information technology (IT) leads to productivity gains and benefits in a wide variety of markets and industries, including healthcare [1–3]. Modern hospitals use IT to transform healthcare delivery processes as a means to improve operational efficiencies, clinical quality, expand access and reduce costs, and increase patient satisfaction, among other benefits [3–9]. A particular IT-enabled innovation in the clinical practice is clinical decision support (CDS). CDS tries to improve the process of decision-making by providing doctors, nurses and

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clinicians with various modes of decision support (e.g., messages, alerts, reminders, consults) following strict clinical guidelines [10, 11]. Many past and recent studies attribute a broad range of benefits to the use of effectively deployed clinical decision support (CDSS) within the hospital enterprise [12, 13], although empirical evidence remains sparse.

Hence, various related factors motivate this work. First, from extant literature has emerged the widely accepted conclusion that IT can be beneficial for hospitals [14]. However, there have been limited studies on the antecedents and conditions underlying robust clinical decision support capability (CDSC) deployments in hospitals. Second, previous studies often have a narrow scope and focus on specific clinical outcomes of specific diseases [11]. Third, the targetted use of IT is becoming more important in hospitals, because it is not uncommon that IT can impede potential benefits [1, 15, 16]. Specifically, IT-productivity literature direct toward the use of IT plans in achieving alignment [17], synchronizing organizations' IT resources to gain benefits [18] and IT spending justifications as part of IT evaluations [18].

Motivated by these factors, this paper follows the premise of resource- and capability synchronization theories [19, 20] and focuses on the IT-driven aspects that enable CDSC in the hospital practice. This aspect is important because this will lead to a broader understanding of IT implementations in hospitals, CDSSs in particular [21]. Specifically, the literature suggested that a particular capability enables information flow and a hospital's information capability (IC) within (en beyond the boundaries of the hospital) and enhance the processes of health information exchange (HIE) [22–24]. This capability is called an information processing capability (IPC) [25]. Hospital's IPC represents their ability to gather complete patient data and information and to enhance clinical processes. Based on the above, we define the following research questions: '*To what extent does an IPC influence a hospital's CDSC?*' and '*What is the conditioning effect of IT alignment on this relationship?*'

This paper applies a positivistic approach whereby we focus on a strong theoretical grounding and research design, evidence, and a logical argument to find support for our central claim. Therefore, our work is structured as follows. We first review the relevant resource-based theory and subsequently propose our research model with the associated hypotheses. Then, we present the methods and results section then follows these sections. We end with our key findings, a discussion of the most important results, and we present some limitations of our current work and provide some direction for future research.

2 Theoretical Ground and Hypotheses Development

2.1 Resources and Capability-Based View

Building upon the resource-based view of the firm (RBV) recent literature contends that modern digital business strategies focus on strategic capability-building and the process of leveraging information systems and information technology (IS/IT) investments; even in healthcare [26–29]. The central premise of resource-synchronization theories within the context of IT is that strategic IT investments in the organization's IT platforms and IT resource portfolio are essential to develop and align firm-wide capabilities to gain benefits and performance enhancements [30–32]. In healthcare, we explicitly see a development the management and decision-makers want to make sure that their resources and investments in IS/IT are harnessed successfully [29]. Hence, hospitals are investing in information flow capabilities to enhance the processes of health information exchange (HIE) [22–24] and to capture a complete patient's picture and their behavior. IPC seems a substantial capability hospital should invest in.

We now follow this resource and capability based view and contend that a hospitals' IPC is deemed appropriate to enhance a hospital's clinical decision support capability (CDSC).

2.2 Information Processing Capability and Clinical Decision Support

IT plays a crucial role in hospitals to improve strategic and operational processes. Following established literature on IPC [33, 34], we know that organizations that have high levels of IPC are better equipped to collect and process internal and external data and information and provide a foundation for decision-making processes. Hence, in this research we regard IPC to represent to core IT-enabled capabilities, i.e., (1) health information exchange (HIE) capability and (2) information capability (IC). We will now elaborate on both of them.

An HIE capability enables hospitals to share and exchange health and patient data and information, e.g., medical reports, PACS images, clinical documentation, and medication lists across the organizations' boundaries [35]. Benefits of sharing information are well elaborated upon in literature, even in the public domain. This capability contributes to primary data and information needs in hospitals and is important for patient management, safety and in clinical decision making [36, 37]. Hence, HIE provides a foundation for hospital efficiency, reducing health care costs, and to enhance patient outcomes [24] by securely exchanging and the use real-time health data and information [22]. Developing an HIE capability allows hospitals to generate a complete patient image, which is essential in for clinical effectiveness, workflow efficiency, and patients' clinical journeys. However, the process of exchanging health information is not enough. It is conceivable that the obtained information needs to be exploited and leveraged even further by a complementary IT-enabled capability to create value in clinical practice. Another essential capability in the dynamic hospital environment is an IC. IC concerns a hospital's capability to acquire information effectively, subsequently view this information and use it in clinical practice. This capability is critical for a patient clinical journey as this is dependent on accurate information and its usage in practice. Such a capability is not restricted to any IT functions or departments [38]. Instead, in our view, IC represents a hospital-wide measure that generates IT/business value and enhanced clinical decision-support levels. Recent research showed that such an IT-enabled capability could only create value if appropriately leverage using a sophisticated IT infrastructure capability [29].

Moreover, various studies argue that hospital operations heavily depend on the process of acquisition, exchanging, analyzing, and use of health data within the organization and within the broader hospital ecosystem [39]. We, therefore, contend that hospitals that develop high levels of IC and HIE are better equipped to deploy and its CDSC in clinical practice. Hence, we contend that hospitals IPC will enhance the clinical decision support within the hospital enterprise and provides value-added services. Therefore, we define:

Hypothesis 1: *IPC is positively associated with a hospital's CDSC.*

2.3 IT Alignment

Investments in IS/IT, along with structured adoption and use, have been suggested to lead to multi-factorial advantages and competitive gains for organizations in various industries [40]. Despite massive investments in IT, organizations quite often fail to achieve improvements in their organizational performance due to their inability to align IT with organizational needs. Ever since the exposition of the 'productivity paradox' [41], organizations increasingly paid attention IS/IT investments, strategic IS/IT planning and its contributions to clinical operations. This development is even more so significant for hospitals, as clinical excellence and service to the community are critical factors for public hospitals [42].

Strategic IS/IT planning that was first addressed by King and Cleland [53] is a crucial activity within organizations and allows organizations to align both business and IT strategies. It is a process by which organizations effectively deploy sustainable business and IT strategies in which internal resources are integrated into external opportunities [43]. Therefore, it enables organizations to assess the existing and planned IS resources and can be regarded as a weapon to involve processes for the identification of opportunities for the use of the IT resources and capabilities [44]. The concept of strategic IT alignment is a central element of strategic IS/IT planning. Both in scientific literature and in practice, it is a well-known fact that achieving a state of IS/IT-alignment is a crucial step to leverage the maximum potential benefits [1, 45, 46], also in healthcare [47]. Literature addresses explicitly the importance of IT plans in achieving alignment [17] and in the process of managing organizations' IT resources [18] and subsequent IT spending justifications [18]. Hence, we define IT alignment as the extent to which hospitals have adequately synchronized their overall IT plan with the IT spending [17, 48]. Now, following both recognized work and more recent studies [46, 49, 50], we argue that the degree of IT alignment will positively influence the relationship between IPC and hospital's CDSC. Hence, we define:

Hypothesis 2: *The higher the degree of IT alignment, the stronger the positive relationship between IPC and CDSC.*

3 Methods

3.1 Data Collection and Sampling Procedure

To assess the proposed research model fit and examine the hypothesized relationships, we needed a high-quality, large-scale, and cross-sectional data. In our systematic search efforts, we found such a comprehensive cross-sectional dataset—the European Hospital

Survey: Benchmarking deployment of e-Health services (2012–2013). This particular dataset contains data from roughly 1,800 European hospitals and is distributed by the European Commission[1]. This survey aimed at benchmarking the level of eHealth adoption and use in acute hospitals across 30 European countries in Europe. In doing so, the research team focused on European acute hospitals and assessed a wide range of aspects from IT applications and the hospitals' IT infrastructure, health data and information exchange, as well as security and privacy issues. The final survey targeted the Chief Information Officers (CIOs) based on their knowledge of the various social, technical and organizational aspects.

Based on the concepts in our research model (see next section) and research scope, we in total conservatively removed 1033 cases with lots of missing data entries. This amount includes removed cases for data consistency and comparability, i.e., private and private not for profit hospitals ($N = 367$) and University hospitals ($N = 196$). These hospitals were removed from our sample as they typically are organized differently (than public hospitals) and have other financing mechanisms. Therefore, our final dataset includes 720 hospitals that represent most European countries. The 720 hospitals can be grouped as follows by firm size-class (based on the number of beds), 13% large (750+ beds), 27% medium (251–750 beds), 51% small (101–250 beds) and 9% micro (less than 100 beds).

To control for common method variance, *ex-post,* we performed Harman's single factor test using SPSS v24. In doing so, we included the relevant constructs in the analysis and found that one specific factor could not attribute to the majority of variance [51]. Hence, this data sample is not affected by CMB.

3.2 Items and Construct Definitions

Our research model's constructs are partly based on and inspired by past foundational, empirical and validated work [17, 29, 33, 35, 52, 53]. For this research, we incorporated a set of twelve survey items from the European Hospital Survey to operationalize HIE. This construct included questions on appointments, receiving laboratory reports, exchanging medical patient data, interaction with patients, transfer prescriptions, and exchange patient medication lists. We operationalized the IC construct by using 17 measurement items from the survey that focused on the use and input of specific clinical information. Hence, this construct includes questions on medication lists, lab, and radiology results, medical history, allergies, immunizations and ordered tests. Finally, we measured CDSC (our dependent construct), using six survey items as a representation of hospitals' capability to enhance the process of clinical decision making. This construct contained the measurements clinical guidelines, drug-drug interactions, drug-allergy alerts, drug-lab interactions, contraindications, alerts to a critical laboratory value. All the above items were measured on or rescaled to a Likert scale from 1 to 5.

[1] This dataset was distributed by the European Commission and is freely accessible through: https://ec.europa.eu/digital-single-market/en/news/european-hospital-survey-benchmarking-deployment-ehealth-services-2012-2013.

Following the core literature, we measured IT alignment as a product of the total hospital's IT budget (Likert scale from 1–5; Less than 1%–5%; More than 5%) and the presence of a formal IT Strategic plan (binary scale). We controlled our outcomes with the control variables 'fte in IT department', 'size' (based on beds), and 'type of hospital' (acute or general).

3.3 SEM Model Specification and Validation

For this research, we use Partial least squares (PLS)-SEM to assess our model's 'outer' and 'inner' model [54, 55]. PLS-SEM is a mature variance-based approach allow us to simultaneously test the measurement model (factor, block analyses) and structural model (to test our hypotheses). For parameter estimation, we use SmartPLS version 3.2.7. [56]. For our measurement model specification, we propose a reflective measurement model (Mode A) for both the first (HIE, CI, and CDSC) and second-order construct (IPC) through which the manifest variables are affected by the latent variables. We also use a bootstrapping procedure with 500 replications to obtain stable results to interpret the structural model. As for sample size requirements, the included data exceeds all minimum requirements.

3.4 Assessment of the Measurement Model

We assessed the psychometric properties of our model by subjecting the first-order constructs to internal consistency reliability, convergent validity, and discriminant validity tests [56]. First, we computed the composite reliability (CR)[2] values for each construct as this measure takes into account the different outer loadings of the manifest variables [54]. As can be seen from Table 1, all our CR values are above the threshold values (i.e., CR $\geq$ 0.7). Next, we assessed all construct-to-item loadings (λ). We removed all manifest indicators with a loading of less than 0.6[3] from our model. In total, we removed seven indicators from the HIE construct, and eight from the IC construct. All indicators for CDSC were above ≥ 0.7.

In PLS model assessments, researchers must evaluate the measurement model by their convergent and discriminant validity [54, 57]. Hence, we examined the convergent validity by examining if the average variance extracted (AVE) is above the lower limit of 0.50 [57]. All values exceed the threshold value. We assessed discriminant validity through different, but related tests. First, we investigated, whether or not, particular cross-loadings load more strongly on other constructs than the outer loading on the associated construct. We also assessed the Fornell-Larcker criterion. In this process, we investigated if the square root of the AVEs of all constructs is larger than the cross-correlation (see entries in bold in Table 1 along the matrix diagonal). As can be seen from Table 1, all correlations among all constructs were below the threshold (0.70) [57]. As a final step in the measurement model assessment, we used a relatively

[2] Composite reliability is similar to Cronbach's alpha without the assumption of the equal weighting of variables.

[3] An even more liberal threshold is a loading value of 0.4 for exploratory studies, see [63].

new heterotrait-monotrait (HTMT) ratio measure of correlations approach by Henseler, Ringle, and Sarstedt [58]. This measure is calculated based on the mean of the correlations of indicators across constructs measuring different constructs, relative to the average correlations of indicators within the same construct. Our assessments show that all HTMT values are well below the 0.90 upper bound. Table 1 shows all relevant outcomes and suggests that our model's first-order reflective measures are now valid and reliable. The next step is to analyze the structural 'inner' model.

Table 1. Model assessment of reliability, convergent and discriminant validity.

	(1)	(2)	(3)	(4)
(1) IT alignment	**n/a**			
(2) Clinical decision support capability	0.101	**0.768**		
(3) Health information exchange	0.041	0.392	**0.751**	
(4) Information capability	0.040	0.412	0.368	**0.751**
AVE	n/a	0.589	0.565	0.564
CR	n/a	0.895	0.866	0.921

4 Analyses and Hypotheses Testing

We used a SmartPLS bootstrapping procedure to test the significance of the various path coefficients in our model. Hence, we found support for our first hypothesis; IPC, indeed, positively influences hospitals' CDSC (β = .482; t = 14.649; p < .0001). As for our second hypothesis (strategic alignment moderates the relationship between IPC and CDSC, H1), we also looked at the significance of the path coefficient (β = 0.101, t = 2.910, p < .005). Hence, we additionally found support for our second hypothesis, while all included control variables showed non-significant effects on CDSC: 'fte IT department' (β = .023, t = 0.998, p = .226), 'size' (β = −.041, t = 1.214, p = .067), and 'type' (β = 0.050, t = 1.839, p = .319). R^2 values, the coefficient of determination, of the endogenous constructs are commonly used to assess model fit [54]. The structural model explains 25.9% of the variance for digital capabilities (R^2 = .259), which is considered moderate to large. We also assessed the model's predictive power [54].

In doing so, we performed a blindfolding procedure (i.e., a sample re-use technique) in SmartPLS and calculated Stone-Geisser (Q^2) [59] values. $Q^2 > 0$ for the endogenous latent constructs indicate that models have predictive relevance. Results show that our Q^2 value (for CDSC) is well above 0 for both cross-validated redundancy (Q^2 = 0.140) and cross-validated communality (Q^2 = 0.423). These outcomes indicated the overall model's predictive relevance [54]. Figure 1 shows the main results of our structural analyses.

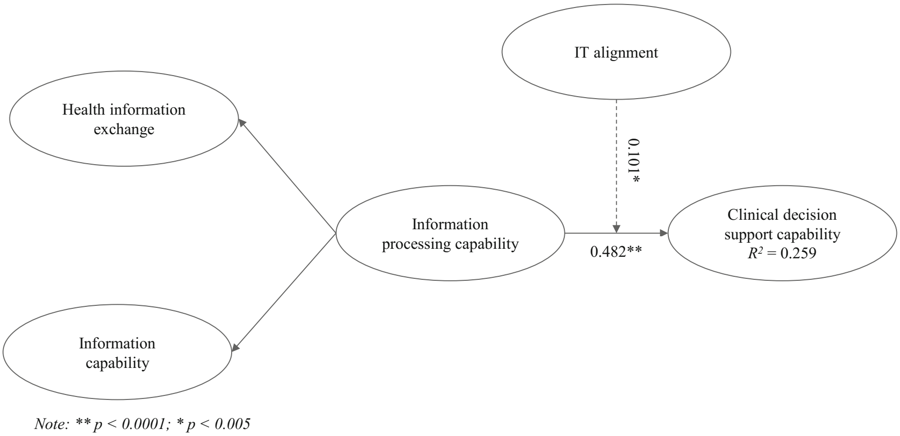

Fig. 1. Structural model analysis.

5 Discussion, Conclusion, and Outlook

This study tried to investigate to what extent an IPC impacts the hospital's CDSC. This research is very relevant because hospitals are currently investing heavily in IT to improve strategic and operational processes. Following the RBV—through which relevant IT assets, resources and capabilities can be identified and assessed toward their importance [60]—we argued that hospitals that have high levels of IPC are better equipped to collect and process internal and external data and information and provide a foundation for decision-making processes. Our PLS results substantiate our claim, i.e., IPC significantly influences CDSC based on a sample of 720 European hospitals.

Moreover, we argued that IT alignment would moderate the relationship between IPC and CDSC based on synchronized IT resources, allocated IT budgets and assets. Next, to empirical evidence for our first hypothesis, we found support for the second claim. IT alignment indeed moderates this relationship and clarifies our model. Like [61], our findings help minimize confusions regarding the role of strategic IT alignment under the resource-based view. These findings are important, as IT not always yields significant productivity gains, also in healthcare [62].

Our outcomes demonstrate relevance for practice as well, as they suggest that greater efficiency gains and operational benefits can be gained through high levels of IPC within the hospital. Hence, IT-enabled processes that drive collaboration, coordination, and innovative diagnostic approaches have great potential to deliver higher quality for patients and physicians at a lower cost. Jones et al. [63] call this 'the definition of greater productivity.' Hospitals can, therefore, enhance CDSC by improving the capability to share and exchange health and patient, and invest in the capability to acquire, view and use information in clinical practice effectively.

Limitations constrain current results, so that future research could seek to address those. First, we focused on public hospitals. Future research might investigate whether or not our results also hold for other types of hospitals. Second, we did not uncover heterogeneity issues, as the scope of our work was limited. However, it is, worth investigating in detail potential differences among groups of hospitals taking into account, e.g., financial incentives for the adoption of IT, organization characteristics, and other potentially related digital capabilities.

To conclude, we believe hospitals can benefit from our results and that they could help decision-makers in the process of allocating their IT budget, resources and asset to facilitate decision-support in clinical practice.

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