# Healthcare costs' reduction through the integration of Healthcare 4.0 technologies in developing economies

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## Abstract

This study aims at examining the effect of Healthcare 4.0 (H4.0) implementation on healthcare costs' reduction in hospitals located in developing economies. For that, 159 middle and senior leaders from hospitals located in Brazil, India, Mexico and Argentina were surveyed regarding their adoption level of H4.0 technologies and cost reduction improvements. Responses were analyzed using multivariate data analysis techniques. Our findings indicate that the adoption of H4.0 technologies, empirically grouped into two different bundles (Sensing-Communication and Processing-Actuation), is positively related to healthcare costs' reduction and that the extent of such relationship may vary according to the bundle under analysis. Our results elucidate the impact of digital integration on healthcare costs, suggesting a cost-effective path based on H4.0 implementation. The identification of this relationship in hospitals located in developing economies evidences the benefits of healthcare digital transformation despite the challenging socioeconomic conditions, which has been contradictorily reported in previous studies.



**Keywords:** Healthcare, Industry 4.0, Healthcare 4.0, Cost reduction, Empirical study.

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## 1. Introduction

Healthcare costs have steadily risen over the past years in the world. According to the World Health Organization – WHO (2019), spending on health is growing faster than the rest of the global economy, accounting for 10% of the global gross domestic product. In low- and middle-income countries (developing economies), such an increasing trend is even more critical as health spending is growing on average 6% annually, compared to 4% in high-income countries (developed economies).

Different aspects may justify the increase in healthcare expenditure in developing economies. The first one is related to increasing population longevity: 65% of the world's population aged 60 or more currently resides in developing countries, and this proportion is expected to rise to 79% by 2050 (United Nations, 2013). Second, there is an increase in chronic illnesses, such as diabetes, heart diseases and neurological disorders, which pressures healthcare costs (Peltzer et al., 2014) and may be partly associated with lifestyle (Rtveladze et al., 2013) and living conditions (Arora et al., 2017) in those countries. Finally, another aspect refers to the rise in medical services' utilization and associated prices. In general, increase in healthcare expenditure is often accompanied by lower levels of efficiency and productivity in healthcare systems (Visconti et al., 2017).

Healthcare organizations have been searching for new solutions and managerial approaches to improve operational effectiveness and reduce costs (Tortorella et al., 2017). The integration of new digital technologies from Industry 4.0 (I4.0) into healthcare organizations has been one of the most

prominent approaches for achieving such results (Ayer et al., 2019). I4.0 promotes interconnectivity and modularity through the adoption of digital technologies, allowing more flexible manufacturing processes and real-time analysis of large amounts of information (Liao et al., 2017; Dalenogare et al., 2018; Xu et al., 2018; Alqahtani et al., 2019). The extension of I4.0 principles to the healthcare context has been named Healthcare 4.0 (H4.0) (Thuemmler and Bai, 2017; Sannino et al., 2018). The implementation of H4.0 enables real-time healthcare customization, resulting in a shift from hospital-centered to patient-centered organizations (Alloghani et al., 2018). H4.0 also supports a more integrated work environment, facilitating synergy across departments to produce efficient patient health outcomes (Bradley et al., 2018; Bergey et al., 2019). Despite these benefits, the high levels of capital expenditure and labor skills associated with H4.0 might discourage its implementation in hospitals located in developing economies.

Few studies have investigated the effect of H4.0 on healthcare costs reduction (e.g. Bardhan and Thouin, 2013; Bates et al., 2014; Wang et al., 2018). Complementarily, Angst et al. (2011) proposed the order in which medical technologies should be integrated to add value to healthcare services in a sample of US hospitals, although not explicitly covering technologies that are part of H4.0 (e.g. cloud computing, big data analytics and Internet of Things). More recently, Okpala (2018) evaluated how technology advances have impacted on healthcare services' costs and patient satisfaction, concluding that the increase in US healthcare expenditure could be associated with technology adoption. In opposition, Wang et al. (2018) carried out a content analysis in 26 case studies reported in the healthcare literature to suggest that H4.0 technologies may promote healthcare costs reduction. Overall, empirical evidence on the effect of H4.0 technologies on healthcare organizations' costs is still scarce and results are contradictory, lacking a clear

indication of cost-effective paths based on H4.0 implementation. In this paper we investigate how H4.0 technologies impact on costs reduction in hospitals located in developing economies, which according to Raghupathi and Raghupathi (2014), Serrano-Santoyo et al. (2014) and Tortorella et al. (2019a; 2020) is a research gap in the current literature on H4.0. In such context, one research question appears as relevant:

RQ. *What is the effect of H4.0 implementation on healthcare costs in hospitals located in developing economies?*

To answer this question and fill this theoretical and empirical gap, we surveyed middle and senior leaders from hospitals located in Brazil, India, Mexico, Argentina with regards to their adoption level of H4.0 technologies and cost reduction improvements. Using multivariate data analysis, we identified H4.0 technologies and their relationship with healthcare costs reduction. This identification allowed the suggestion of cost-effective paths based on H4.0 implementation, despite contrary socioeconomic aspects faced by hospitals located in developing economies. Our approach is framed on General Systems Theory – GST (Kast and Rosenzweig, 1972; Skyttner, 2005), which assumes that a system is a cohesive conglomeration of interrelated and interdependent elements (i.e. H4.0 technologies and healthcare costs) influenced by its environment (i.e. developing economies' context). GST also states that a goal (i.e. healthcare costs reduction) can be achieved in many ways, and the proper understanding of system's elements elucidates the most effective means for achieving such goal.

The rest of this paper is structured as follows. Section 2 presents a literature review on the main concepts related to our study, which culminate in the formulation of the investigated hypotheses. Section 3 describes the proposed method, whose results are shown in Section 4 and discussed in

Section 5. Practical and theoretical implications of our research are presented in Section 6, together with limitations and future research opportunities.

## 2. Literature review and hypotheses

### 2.1. Healthcare costs in developing economies

Healthcare costs are a fundamental and rising problem in economic and social terms in developing economies. Total health spending is growing faster than the global gross domestic product. According to WHO (2018), between 2000 and 2016 low- and middle-income countries experienced an increase in the per capita public spending in health from approximately US$ 30 and US$ 130 to US$ 58 and US$ 270, respectively, in real terms. Healthcare systems in these countries are also facing challenges such as the burden of rising and aging populations and the delivery of adequate healthcare to population. The impact of this challenging context is that one-third of all global health expenditure is expected to occur in developing economies by 2022 (World Economic Forum, 2014). Peltzer et al. (2014) indicated that economic factors, such as higher economic or wealth status, financial support, and health insurance are associated with healthcare utilization, which tends to be aggravated in developing economies.

Governments in low- and middle-income countries cover on average of 22% and 51% of health costs, respectively, while more than 35% of health spending per country comes from out-of-pocket expenses (The Geneva Association, 2019). More specifically, Jakovljevic et al. (2017) analyzed data from BRICS (Brazil, Russia, India, China and South Africa) nations and indicated that their average health expenditure grew from 5.41% of their GDP in 1995 to 6.94% in 2013. However, such expenditure is forecasted to reach an average of 7.86% by 2025, and healthcare organizations

in those countries will be forced to manage rising patient volumes through more efficient processes. O'Donnell (2007) emphasizes that, in addition to the high values charged by healthcare providers, travel costs are relevant for consuming healthcare in developing economies, especially in rural areas where distances to healthcare facilities and the poor condition of roads represent a significant issue.

The Global Program on Evidence for Health Policy carried out by the WHO (2011), also known as WHO-CHOICE, estimates unit costs for general healthcare organizations at patient and program levels for health interventions in all regions of the world. Patient costs represent those incurred at the point of delivery of healthcare interventions, such as the cost of a lab test, outpatient visit or surgery (Adams et al., 2008); program costs are the ones related to overhead or general administrative activities, such as planning, supervision, training, media and outreach (Mulligan et al., 2003; Vo et al., 2018). The ratio between patient and program costs can vary significantly according to hospitals' characteristics which undermines any generalization (Uyar and Neyis, 2015), even though the hospitals' socioeconomic context (developing economies) may be similar (Jakovljevic et al., 2017). Overall, healthcare costs became a key public policy (Dahlgaard et al., 2011), as well as hospital management in developing economies.

### 2.2. Integration of digital technologies into healthcare – H4.0

The advent of Industry 4.0's technological revolution appears as a promising solution to the healthcare costs' global challenge. The integration of information technologies into healthcare organizations is not a recent phenomenon. Back in 1920s, healthcare professionals started using medical records to document details, complications, and outcomes of patient care. Paper records were used until the 1960s, when technological innovations (e.g. use of computers) led to new

approaches to standardize and share medical data (VertitechIT, 2019). The introduction of desktop personal computers in the late 1970s and beginning 1980s ushered the modern age of digital technologies, which culminated in novel solutions in the healthcare sector (Dehe and Bamford, 2017). Subsequently, in 1990s, the relevance of digital technologies was drastically increased by the advent of Internet, which gave origin to the term “e-health” or “smart health” (Aceto et al., 2018). More recently, healthcare organizations are moving along with the Fourth Industrial Revolution era, being characterized by an increasing level of interconnected technologies that allow more effective therapeutic structures and supporting processes (Sultan, 2014; Yang et al., 2015).

Although much emphasis has been put on the technicalities that made feasible H4.0 implementation, such as price, size, capacity and portability of digital technologies (Prieto González et al., 2016; Oppong et al., 2018), it is important that hospitals shift from a technology-centered to a patient-centered approach, culminating in changes in organizational structures, strategies and culture (Alloghani et al., 2018). In this sense, H4.0 implementation does not only entail a significant technical change, but implies a reorganization of hospitals so that technologies may be adapted to social needs, such as patients’ and caretakers’ beliefs and constraints (Kochan et al., 2018; Pan et al., 2018; Bergey et al., 2019). Particularly in developing economies, integration of digital technologies into healthcare is at an early stage in some African, Asian and Latin American countries. Evidence of this integration is growing based on a common belief that digital technologies may help solving key healthcare issues (GSMA Intelligence, 2017).

The increasing investment in new digital technologies by the healthcare industry calls for a deeper understanding of technology management (Angst et al., 2011; Aoun and Hasnan, 2017), especially in the light of I4.0. In fact, from a technology management perspective (Khan and Wood, 2015;

Cetindamar et al., 2016), much still needs to be understood on how to develop, adapt, exploit and integrate different digital technological capabilities to promote an effective H4.0 implementation. Such understanding is aligned with assumptions from GST (Caws, 2015), as there may not be a universal roadmap to H4.0 implementation. Although the concurrent implementation of different H4.0 technologies is claimed to promote systemic benefits (Yang et al., 2015; Yuehong et al., 2016), their interrelationship might impose nontrivial implementation challenges, and research on this regard has not yet received adequate attention (Serrano-Santoyo et al., 2014; Tortorella et al., 2019a; 2020). The diversity of H4.0 technologies available has been evidenced in the scoping review conducted by Tortorella et al. (2019a), which listed nine digital technologies considered as part of H4.0 portfolio; they are: (*i*) big data, (*ii*) Internet of Things (IoT), (*iii*) biomedical/digital sensors, (*iv*) cloud computing, (*v*) remote control or monitoring, (*vi*) collaborative robots, (*vii*) augmented reality, (*viii*) 3D printing, and (*ix*) machine learning. We considered these technologies to design our empirical study.

### 2.3. H4.0 and healthcare costs

GSMA Intelligence (2017) suggests that initiatives aimed at integrating digital technologies into healthcare in developing economies should focus on three main objectives: (*i*) expand coverage and access; (*ii*) improve services quality; and (*iii*) reduce and optimize cost. In terms of access, digital technologies allow a wider reach of healthcare delivery as some services (e.g. patient monitoring and diagnosis) may be performed and managed remotely. Digital technologies enable greater and faster patient access to their health information via mobile (Gomez-Sacristan et al., 2015). As far as quality is concerned, H4.0 facilitates faster and more effective coordination of care services and health professionals as well as more effective data sharing, allowing for earlier

detection of risks and targeted provision of health information services (Wang et al., 2018). Cost efficiency is also supposed to improve, since the transition from paper to digital may ensure that available health resources are used where and when needed (Bradley et al., 2018); that includes the digitization of drug inventory, supply chain and patient records (Ali et al., 2018).

However, evidence about the impact of digital technologies integration on healthcare costs is inconclusive, and the net effect of H4.0 implementation remains uncertain (Angst et al., 2011; The Geneva Association, 2019). On one hand, new technologies enable medical and processes advances which extend the scope, range and quality of healthcare, increasing expenditure (Barbash, 2010; Agha, 2014; Okpala, 2018); on the other hand, biomedical sensors, IoT and other technological innovations promote cost efficiency (Blaya et al., 2010; Buntin et al., 2011), suggesting a promising scenario for healthcare costs' reduction (Bardhan and Thouin, 2013). The poor literature evidence linking H4.0 to cost reduction is particularly scarce when focusing on developing economies, due to socioeconomic challenges (Piette et al., 2012; Serrano-Santoyo et al., 2014; Tortorella et al., 219a; 2020). Aiming at bridging that gap, we propose the following hypothesis:

H1: *The adoption of H4.0 technologies positively impacts costs reduction in hospitals located in developing economies.*

## 3. Method

An empirical approach was applied to answer the research question. We followed the survey method as it allows a high level of representativeness, low cost, potential statistical significance and standardized stimulus to all respondents (Montgomery, 2013). The proposed method consists of four main steps: (*i*) sample characteristics and data collection; (*ii*) instrument development; (*iii*)

construct reliability and validity; and (*iv*) data analysis. These steps are detailed in the subsequent sections.

### 3.1. Sample characteristics and data collection

As the study was carried out by a group of researchers from different countries, a transnational survey was conducted with hospitals located in Brazil, Argentina, Mexico, and India. Although falling in the emerging economy category, these countries differ in population, per-capita gross domestic product and national language, increasing the generalizability of our results. Hospitals sampled were already partners of the authors in previous research or consultancy activities, which facilitated the initial contact and openness to data collection. Since these hospitals were benchmarks in their locations and were undergoing a digital transformation, we assumed that they would provide a reasonable representation of the investigated topic. Multiple responses per hospital were gathered to curb issues related to single-respondent bias (Hair et al., 2104) and enhance internal validity and reliability of the research (Brewer and Crano, 2000; Tabachnik and Fidell, 2013). These respondents were middle and senior managers of their hospitals, leading clinical or non-clinical departments. Due to this background diversity, a brief description of H4.0 technologies and application examples were provided together with the questionnaire, mitigating misinterpretations on the involved concepts (Kothari, 2004). All respondents were associated to tertiary care hospitals with similar complexity levels.

Data was gathered during May and June 2019. Each researcher accessed their respective network, which was built over time based on previous research and consultancy activities. Respondents were informed upfront that participation was voluntary and that there were no right answers. The final sample consisted of 159 responses from 16 hospitals (approximately 9.9 respondents per

hospital). 42.1% of the sample was from Brazil, with respondents from 9 hospitals. Respondents were mainly supervisors or coordinators (74.2%) with more than 2 years of experience in their roles (79.9%). With regards to department types, 57.2% of the surveyed respondents led clinical departments (see Table 1).

Table 1 – Sample characteristics (*n* = 159)

### 3.2. Instrument development

The questionnaire was comprised of three parts (see Appendix A). The initial part gathered demographic characteristics of respondents and their hospitals. The second part assessed the adoption level of nine digital technologies suggested by Tortorella et al. (2019a) in the respondents' hospitals. The adoption level of these technologies was considered a proxy for H4.0 implementation; since the exact concept of H4.0 may still be vague to respondents, representing H4.0 through its associated technologies tends to prevent erroneous answers. A Likert scale that varied from 1 (not used) to 5 (fully adopted) was used. The third part asked about the perceived improvement level related to healthcare cost reduction within hospitals over the past three years. As financial results are often carefully protected by organizations, using managers' perception on healthcare cost reduction facilitated access to that information. A similar approach to curb organizational confidentiality has been used in Tortorella et al. (2019b). A five-point scale ranging from 1 (worsened significantly) to 5 (improved significantly) was used. Seven experts (four scholars and three practitioners) verified the design and quality of the questionnaire before its application, which resulted in minor taxonomy adjustments. The inclusion of a glossary with examples as an appendix to the questionnaire was also suggested.

Reliability of the responses related to H4.0 technologies was checked through Cronbach's alpha calculation; the obtained value of 0.841 was above the recommended threshold of 0.6 (Meyers et al., 2006). To address common method bias and prevent from covariation, different scale anchors were adopted (Podsakoff et al., 2003). We also added a statement indicating that responses would be treated anonymously. Finally, Harman's single-factor test (Malhotra et al., 2006) was carried out indicating that all variables loaded into one factor that explained 30.5% of the variance. Hence, we disregarded any potential issues related to common method bias.

### 3.3. Construct reliability and validity

A Principal Component Analysis (PCA) with varimax rotation was performed to extract orthogonal components using responses to the adoption level of H4.0 technologies. Two principal components were retained using Kaiser's criterion (i.e. components with eigenvalues equal to or larger than 1.0 are retained), accounting for approximately 56% of the total variance (see Table 2), which is slightly lower than the 60% recommended by Härdle and Simar (2015). We also carried out a scree plot analysis of factors' eigenvalues; when ordered from largest to smallest, the plot displayed a downward curve with an inflection after the second eigenvalue, leading to the two factors used in our analysis (Cattell, 1966). of factors, displaying the eigenvalues in a downward curve and ordering them from largest to smallest (Cattell, 1966). In view of these evidences, we assumed that two factors were sufficient to represent the variance of the observed variables.

From the analysis of variables loadings (values > 0.45 were indicative of the variable's pertinence to the component; Hair et al., 2014) and supported by the conceptual proposition of Aceto et al. (2018), two bundles of digital technologies were empirically identified according to their predominant roles. The first bundle, which comprised digital technologies applied for capturing

and communicating data about a patient, equipment, material or process, was denoted as ‘Sensing-Communication’. The second bundle, named ‘Processing-Actuation’, consisted of technologies that can process such data and transform it into actual information, moving or controlling a system, mechanism or software. Reliability of components was checked based on their respective Cronbach's alpha and composite reliability (CR) values, which were all larger than 0.6 and 0.7, respectively (Meyers et al., 2006; Tabachnik and Fidell, 2013). Responses for each bundle were obtained calculating a weighted average of original responses using factor loadings as weights. Such values were later standardized to avoid scale effects and given in a continuous scale.

Table 2 – PCA to validate constructs of H4.0 technologies ($n$ = 159)

### 3.4. Data analysis

Since two constructs of H4.0 technologies were empirically identified, we checked their direct and indirect (mediating) effects on healthcare costs’ reduction to verify hypothesis H1, performing a set of Ordinary Least Square (OLS) hierarchical linear regressions (Härdle and Simar, 2015). For each hypothesized mediation to healthcare cost reduction (dependent variable), different models were examined. In this sense, both *Sensing-Communication* and *Processing-Actuation* technologies were tested as either independent or mediating variables depending on the model. Three control variables were considered: (*i*) respondent’s department type (0 = non-clinical; 1 = clinical), (*ii*) hospital’s management type (0 = public; 1= private) and (*iii*) healthcare organization (16 different hospitals). Our dataset was nested (mean of 9.9 respondents per hospital) and responses from the same hospital could be correlated, leading to misguiding results. To check this

association, we created one dummy variable for each healthcare organization and included these 16 dummies in the regression analyses (Montgomery, 2013).

Multicollinearity was verified determining the variance inflation factors (VIF) of all variables. Because all VIF values were below 5.0, multicollinearity was not considered a problem (Belsley et al., 2005). We also tested assumptions on normality, linearity and homoscedasticity between independent, mediating and dependent variable, following Hair et al.'s (2014) indications. We analyzed residuals to check normality of errors (see Appendix B); linearity was assessed with plots of partial regression for each model; for homoscedasticity, standardized residuals were plotted against predicted value and visually examined (Tabachnik and Fidell, 2013). All tests satisfactorily met the OLS regression requirements. Pairwise correlations between all variables (control, independent and dependent) were also determined; they are displayed in Table 3. Significant correlation coefficients ($p$-value < 0.05) were found positive or negative, indicating the nature of the association between variables (Meyers et al., 2006).

Table 3 – Pairwise correlation coefficients

Following indications from Montgomery et al. (2012), we randomly split the dataset into two portions keeping the proportions of answers from each country in the splitting. The first portion, comprised of 80% of the data (training set; $n_1$ = 127), was used for building the hierarchical regression models. The second portion, composed of the remaining 20% of the dataset (testing set; $n_2$ = 32), was used for testing/validating the selected models. The validation procedure followed indications from Meneghini et al. (2018), which suggested the use of a differentiation index I, given by the ratio between the model's coefficient of determination $R^2$ and its mean absolute

percentage error (MAPE), for choosing the best among candidate models. $R^2$ values range between 0 and 100% (larger is better), and there is no universally accepted minimum threshold value for the indicator, which depends on the application (Glantz and Slinker, 1990). MAPE is one of the most used measures to verify the accuracy of a predicting model due to its advantages of scale independence and interpretability (Kim and Kim, 2016). Reduced MAPE values are desired, since they indicate good predictive capacity of the model. Two mediation models were examined, and predictions obtained from each model using the test dataset were compared. The model with highest *I* value was chosen to predict the improvement on healthcare cost reduction (dependent variable).

## 4. Results

Table 4 displays the OLS regression models' standardized coefficients for the testing data. Since none of the 16 dummies determined for controlling healthcare organizations presented a significant effect on the dependent variable, we simplified results and disregarded reporting their coefficients in the analyses.

Regardless of the mediation's orientation, our results indicate that both bundles of digital technologies are mutually synergistic. In other words, as the adoption level of *Processing-Actuation* technologies increases so does the level of *Sensing-Communication* ($\hat{\beta}$ = 0.445; *p*-value < 0.01), and vice-versa ($\hat{\beta}$ = 0.446; *p*-value < 0.01). These results indicate that both bundles of technologies are equally benefitted by their extensive adoption and do not conflict with each other. Such outcomes are somewhat coherent with the indications from Riva et al. (2012) and Amendola et al. (2014), which have suggested that the integration of different and complementary digital

technologies allows a more systemic digital transformation of healthcare organizations. More specifically, Aceto et al. (2018) have conceptually proposed that the bundles of H4.0 technologies are not disjoint, presenting roles that can be either common or complementary in their nature. Results from our empirical study support such conceptualization.

However, when analyzing the direct and indirect (mediating) effects of each bundle of technologies on healthcare costs' reduction, different results are observed. The first analysis considered *Sensing-Communication* as the mediator of the relationship between *Processing-Communication* and *Healthcare Cost Reduction*. Although Model 1A indicated a significant model for the control variables ($F$-value = 4.268; $p$-value < 0.05), the addition of the independent (Model 1B) and mediating (Model 1C) variables led to models with better fit (i.e. the change in $R^2$ values was significant in both models) and Model 1C was selected as it explained the highest percentage of the variance ($F$-value = 11.588; $p$-value < 0.01; adjusted $R^2$ = 0.252). In Model 1C, management type ($\hat{\beta}$ = 0.213; $p$-value < 0.01) and *Sensing-Communication* technologies ($\hat{\beta}$ = 0.403; $p$-value < 0.01) had a significant positive influence on healthcare cost reduction. Despite the significant direct effect of *Processing-Actuation* on healthcare cost reduction displayed in Model 1B ($\hat{\beta}$ = 0.305; $p$-value < 0.01), such effect seems to be less extensive when *Sensing-Communication* technologies are concurrently adopted. That suggests that *Processing-Actuation* have an indirect positive effect on healthcare cost reduction through the adoption of *Sensing-Communication* technologies, which indeed act as mediator.

The second analysis tested the mediating effect of *Processing-Actuation* on the relationship between *Sensing-Communication* and healthcare costs' reduction. Similar to the previous analysis, the predicting capacity of Model 2A (only control variables) was significantly outperformed (change in $R^2$ = 0.199; $p$-value < 0.01) by Model 2B, which included *Sensing-Communication* as

the independent variable. However, adding the mediating variable (Model 2C) led to no significant improvement in fit, and Model 2B was chosen. These results indicate that *Processing-Actuation* technologies are not mediators of this relationship. The analysis also suggests that *Sensing-Communication* technologies have a positive direct effect ($\hat{\beta}$ = 0.459; *p*-value < 0.01) on healthcare cost reduction. Hence, *Sensing-Communication* not only positively mediates the relationship between *Processing-Actuation* and healthcare costs' reduction (evidenced in the first analysis), but it also presents a direct and positive effect on the latter.

Table 4 – Standardized $\hat{\beta}$ coefficients for hierarchical regression analyses (training data)

To validate Models 1C and 2B and compare their accuracy, different predictions for healthcare cost reduction were performed using each model's unstandardized coefficients on the testing portion of the dataset; resulting MAPE and *I* values are presented in Table 5. Although Model 1C presented a slightly higher $R^2$ value, Model 2B was more accurate (MAPE = 0.215). Overall, both models could be validated displaying similar prediction capacities and accuracies (*I* = 1.244 and *I* = 1.223, respectively). That suggests that both the direct effect of Sensing-Communication and the indirect effect of Processing-Actuation are relevant to explain healthcare cost reduction. Despite the relatively low adjusted $R^2$ values of Models 1C and 2B (0.252 and 0.245, respectively), results indicate that the implementation of H4.0 technologies partially explains the cost reduction observed in those hospitals. In other words, our findings point that H4.0 technologies do have a positive impact on cost reduction, but there may be other organizational aspects and practices that may also explain cost performance in those hospitals.

Table 5 – $R^2$, MAPE and $I$ for models 1C and 2B (testing data)

## 5. Discussion

The obtained results, which are summarized in Figure 1, have provided interesting insights that are further discussed now. It is worth framing the evolution of technology adoption to shed light on the potential mechanisms behind the observed results. Digital technologies that aim to capture and communicate data in healthcare organizations, such as remote control or monitoring and biomedical/digital sensors, have been long investigated (Van Dam et al., 2001; Yuehong et al., 2016). Andreu-Perez et al. (2015) discuss the application of these technologies in healthcare, classifying its evolution in three generations. In first-generation applications, the architectural system typically consisted of a single sensing modality with wireless connectivity, being able to make predictions about activities or health status. Processing of data was typically performed centrally, relying on offline, retrospective batch processing (Postolache et al., 2013). The second generation emerged as a result of advances in sensing technologies that facilitated continuous monitoring with multiple sensors, each of them being responsible for providing inference, either from wearable or ambient sensors (McGrath et al., 2014). This generation introduced processing entities that, in addition to sensing, took the necessary actions toward an objective. The third generation combined continuous health monitoring with other sources of medical knowledge, integrating with technologies responsible for extracting information from a variety of sources including clinical research, patient records, laboratory generated data (e.g. *Processing-Actuation* technologies).

The effect of this evolution may be also due to the higher pervasiveness of *Sensing-Communication* technologies in healthcare organizations, as their mean adoption level (see Table

2) was considerably higher than that of *Processing-Actuation* technologies. In this sense, hospitals in developing economies seem to be more familiar with *Sensing-Communication* technologies, which are more extensively adopted and whose benefits (e.g. cost reduction) have been longer examined. Such fact may justify why *Sensing-Communication* technologies present a significant direct and indirect (mediating) effect on healthcare costs' reduction. However, as the adoption of *Processing-Actuation* technologies positively impacts *Sensing-Communication*, their effect on healthcare costs is relevant for a systemic improvement. In other words, although *Processing-Actuation* technologies appear to have a less extensive influence on healthcare costs' reduction, their adoption cannot be neglected.

Another explanation may be found in Frank et al. (2019), which suggested that some *Sensing-Communication* technologies, such as Big Data, IoT and Cloud Computing, act as a fundamental basis for digital transformation in organizations. The establishment of such infrastructure allows the integration of other digital technologies that together will contribute to more efficient processes, services and products. Such structure was later empirically validated by Tortorella et al. (2019a), which confirmed the importance of *Sensing-Communication* technologies (denoted as base technologies) for organizational learning. Although these studies were carried out in a manufacturing context, the relevance of the role played by *Sensing-Communication* technologies was also verified. We argue that the adoption of this kind of technologies from a system-wide perspective enables hospitals to significantly reduce their costs, especially the ones located in developing economies.

Figure 1 – Empirically validated relationships

## 6. Conclusions

This study aimed at examining the effect of H4.0 implementation on healthcare costs' reduction in hospitals located in developing economies. Our results yielded significant contributions to both theory and practice, which are subsequently described.

In terms of theoretical implications, our study empirically evidenced the positive effects of H4.0 implementation on healthcare costs' reduction. Although the integration of digital technologies into healthcare organizations is a growing research topic, few studies have explicitly approached its impact on cost reduction, and results are inconclusive and, sometimes, contradictory. Our results demystified this relationship, indicating that H4.0 technologies adoption can reduce costs even in hospitals located in challenging socioeconomic contexts, such as developing economies. However, not all H4.0 technologies may present the same extent of influence, varying according to their roles within healthcare organizations (i.e. *Sensing-Communication* or *Processing-Actuation*). From the perspective of the General Systems Theory (Kast and Rosenzweig, 1972; Caws, 2015), our research sheds light on the interrelationship between H4.0 technologies, indicating their synergistic association and reinforcing the need for their concurrent adoption to fully obtain the desired benefits (i.e. healthcare costs' reduction). In other words, the bundles of H4.0 technologies present different effects on healthcare costs' reduction in developing economies. Hence, our study evidences the most cost-effective implementation path for these technologies, which is aligned with assumptions from General Systems Theory.

With regards to practical contributions, this research provides arguments to hospital managers about the reduction in costs that could be derived from H4.0 implementation. More specifically, our findings indicate that healthcare organizations in developing economies may also benefit from digital technologies adoption. Since capital expenditure capacity is a typical constraint for

hospitals located in developing economies (Chen et al., 2019; Luthra et al., 2019), the more prominent effects of *Sensing-Communication* technologies on cost reduction guide managers to prioritize H4.0 where economic benefits may be maximized. However, that does not exclude the adoption of *Processing-Actuation* technologies, since they reinforce the implementation of *Sensing-Communication* and have an indirect effect on costs reduction.

Some limitations of this investigation bring opportunities for future research. Although falling in the developing economy category, the countries involved in this study (Brazil, Argentina, Mexico and India) differ in population, per-capita gross domestic product and national language. On one hand, these characteristics may entail socioeconomic specificities that can influence respondents' perception; on the other hand, the empirical verification of the relationship between H4.0 implementation and healthcare costs' reduction using a dataset comprised by different developing economies increases the generalizability of our results. Another drawback of our research is the non-utilization of actual costs data. Because access to and sharing of information related to financial data is generally restricted, we used managers' perception on the improvement level of healthcare costs' reduction. The development of future studies encompassing actual costs data could raise not only more assertive insights, but also allow the establishment of a longitudinal analysis on H4.0 implementation. Finally, it is worth mentioning that future research could increase the data collection in order to obtain a larger sample size. Such limitation could be addressed in terms of both number of hospitals and number of respondents per hospital.

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## Figures

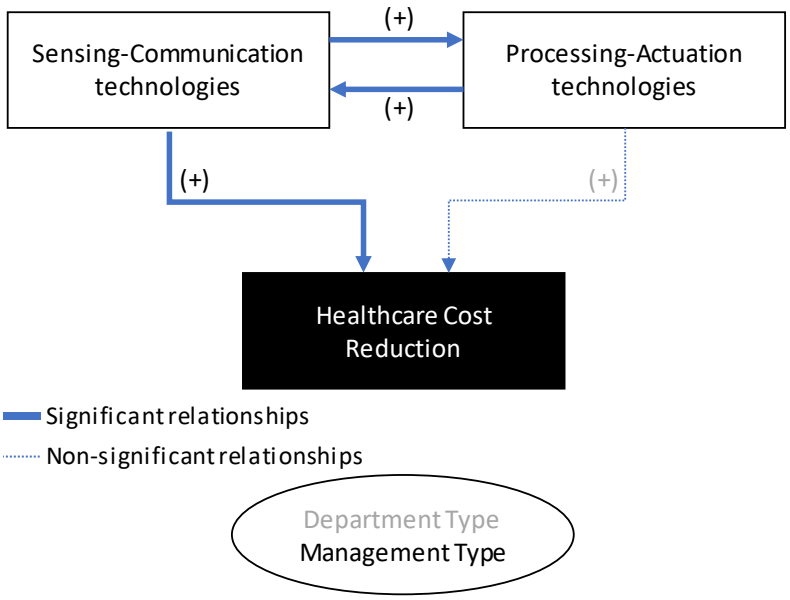


Figure 1 – Empirically validated relationships

# Tables

Table 1 – Sample characteristics ($n$ = 159)

| Country | | | | | Department type | | | Respondent's experience | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Hospitals | | Respondents | | Non-clinical | 68 | 42.8% | Less than 2 years | 32 | 20.1% |
| Brazil | 9 | 56.2% | 67 | 42.1% | Clinical | 91 | 57.2% | More than 2 years | 127 | 79.9% |
| India | 4 | 25.0% | 36 | 22.6% | Management type | | | Respondent's role | | |
| Mexico | 2 | 12.5% | 34 | 214% | Public | 70 | 44.0% | Supervisor or Coordinator | 118 | 74.2% |
| Argentina | 1 | 6.3% | 22 | 13.8% | Private | 89 | 56.0% | Manager or Director | 41 | 25.8% |

Table 2 – PCA to validate constructs of H4.0 technologies ($n$ = 159)

| H4.0 technologies | Mean | Std. Dev. | Commonalities | Sensing-Communication | Processing-Actuation |
|---|---|---|---|---|---|
| Big Data | 2.13 | 1.39 | 0.592 | **0.725** | |
| IoT | 2.67 | 1.54 | 0.520 | **0.715** | |
| Biomedical/Digital Sensors | 2.97 | 1.37 | 0.498 | **0.705** | |
| Cloud Computing | 2.65 | 1.46 | 0.501 | **0.697** | |
| Remote Control or Monitoring | 2.14 | 1.31 | 0.519 | **0.574** | |
| Collaborative Robots | 1.41 | 1.01 | 0.729 | | **0.829** |
| Augmented Reality | 1.64 | 1.07 | 0.653 | | **0.788** |
| 3D Printing | 1.56 | 1.03 | 0.385 | | **0.619** |
| Machine Learning | 1.70 | 1.19 | 0.621 | 0.509 | **0.601** |
| Eigenvalue | | | | 3.697 | 1.320 |
| Initial percent of variance explained | | | | 41.083 | 14.669 |
| Rotation sum of squared loadings (total) | | | | 2.685 | 2.333 |
| Percent of variance explained | | | | 29.830 | 25.923 |
| Cronbach's alpha ($n$ = 159) | | | | 0.757 | 0.741 |
| Composite reliability (CR) | | | | 0.757 | 0.743 |
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy | | | | 0.834 | |
| | | Approx. Chi-Square | | 421.303 | |
| Bartlett's Test of Sphericity | | Degrees of freedom | | 36 | |
| | | Significance ($p$-value) | | 0.000 | |

Extraction method: principal component analysis. Rotation method: varimax with Kaiser normalization. Factor loadings below 0.45 were omitted.

Table 3 – Pairwise correlation coefficients

| Variables | 2 | 3 | 4 | 5 |
|---|---|---|---|---|
| 1-Healthcare cost reduction | 0.294** | 0.257** | 0.049 | 0.172* |
| 2-Sensing-Communication technologies | - | 0.566** | 0.214** | -0.254** |
| 3-Processing-Actuation technologies | | - | 0.138 | -0.040 |
| 4-Department type | | | - | -0.331** |
| 5-Management type | | | | - |

Note: * Correlation coefficient significant at 5%; ** Correlation coefficient significant at 1%.

Table 4 – Standardized $\hat{\beta}$ coefficients for hierarchical regression analyses (training data)

| Mediator | Variables | Sensing-Communication | Healthcare Cost Reduction | | |
|---|---|---|---|---|---|
| | | | Model 1A | Model 1B | Model 1C |
| Sensing-Communication technologies | Department type | 0.164** | 0.093 | 0.036 | -0.030 |
| | Management type | -0.026 | 0.264*** | 0.202** | 0.213*** |
| | Processing-Actuation | 0.445*** | | 0.305*** | 0.125 |
| | Sensing-Communication | | | | 0.403*** |
| | *F*-value | 13.215*** | 4.268** | 7.369*** | 11.588*** |
| | $R^2$ | 0.244 | 0.064 | 0.152 | 0.275 |
| | Adjusted $R^2$ | 0.225 | 0.049 | 0.132 | 0.252 |
| | Change in $R^2$ | | | 0.088*** | 0.123*** |
| | Variables | Processing-Actuation | Healthcare Cost Reduction | | |
| | | | Model 2A | Model 2B | Model 2C |
| Processing-Actuation technologies | Department type | 0.075 | 0.093 | -0.021 | -0.030 |
| | Management type | 0.173** | 0.264*** | 0.235*** | 0.213*** |
| | Sensing-Communication | 0.446*** | | 0.459*** | 0.403*** |
| | Processing-Actuation | | | | 0.125 |
| | *F*-value | 13.082*** | 4.268** | 14.662*** | 11.588*** |
| | $R^2$ | 0.242 | 0.064 | 0.263 | 0.275 |
| | Adjusted $R^2$ | 0.223 | 0.049 | 0.245 | 0.252 |
| | Change in $R^2$ | | | 0.199*** | 0.012 |

Notes: * Significant at 10% (p-value < 0.10); ** Significant at 5% (p-value < 0.05); *** Significant at 1% (p-value < 0.01).

Table 5 – $R^2$, MAPE and *I* for Models 1C and 2B (testing data)

| Model | Independent variable | Mediator | Constant value [b] | $R^2$ | MAPE | *I* |
|---|---|---|---|---|---|---|
| 1C | Processing-Actuation | Sensing-Communication [a] | 2.883 | 0.275 | 0.221 | 1.244 |
| 2B | Sensing-Communication [a] | Processing-Actuation | 2.845 | 0.263 | 0.215 | 1.223 |

Notes: [a] Significant coefficient in the regression model. [b] Unstandardized β coefficients presented.

# Appendix

## Appendix A – Questionnaire and glossary of terms

This questionnaire aims at understanding the implementation level of digital technologies in your HOSPITAL. Respondents will be kept anonymous and responses will be treated confidentially. There is no right or wrong answer. Thank you very much for your participation!

1- Please, fill below with the following information:

a) Your role within the hospital: ( ) Supervisor or Coordinator ( ) Manager or Director

b) Your experience: ( ) Less than 2 years ( ) More than 2 years

c) Your department type: ( ) Clinical ( ) Non-clinical

d) Your hospital ownership: ( ) Public ( ) Private

e) Country where your hospital is located: _____

2- Please, indicate below the adoption level of the following digital technologies in your hospital:

*Scale: from 1 (not used) to 5 (fully adopted)*

| **Digital Technology** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| Machine Learning | | | | | |
| Biomedical/Digital Sensors | | | | | |
| Collaborative Robots | | | | | |
| 3D Printing | | | | | |
| Big Data | | | | | |
| Internet of Thing | | | | | |
| Augmented Reality | | | | | |
| Cloud Computing | | | | | |
| Remote Control or Monitoring | | | | | |

3- Please, indicate below the perceived improvement level related to healthcare cost reduction within your hospital over the past three years:

*Scale: from 1 (worsened significantly) to 5 (improved significantly)*

| Improvement | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Cost reduction | | | | | |

**Glossary:**

*Digital and / or Biomedical Sensors:* A digital sensor is a device capable of detecting physical or chemical quantities, called instrumentation variables, and transforming them into electrical variables. Examples of instrumentation variables are: temperature, light intensity, distance, acceleration, inclination, displacement, pressure, force, torque, humidity, movement, and pH. Examples of digital and/or biomedical sensors in hospitals are: pacemakers, insulin pumps, pressure meters, and oximeters.

*3D Printing:* 3D printing is performed using a computer to apply layer upon a layer of a specific material (e.g. plastic, metal) to construct a desired object. 3D printing is used for the development of new surgical cutting and drill guides, prosthetics, as well as the creation of patient-specific replicas of bones, organs, and blood vessels. Examples of 3D printing include 3D-printed skin for burn victims, 3D-printed heart, 3D-printed insoles, and 3D-printed face.

*Collaborative Robots:* Collaborative robots in healthcare may be used for surgical or non-surgical purposes. The da Vinci surgical system is one example of surgical system that provides multi-quadrant access and is used for a variety of complex procedure within operating rooms. Non-surgical collaborative robots incorporate automation to some repetitive, delicate and time-consuming activities including dosing, mixing and pipetting tasks or loading centrifuges.

*Internet of Things (IoT)* is a system of interrelated computing devices, mechanical and digital machines, objects, or people who have unique identifiers and the ability to transfer data through a network, without requiring human-to-human or human-to-computer interactions. Examples of IoT in hospitals are systems to detect where the equipment is physically located or glucose monitoring systems.

*Big Data* is a term that describes any voluminous amount of structured, semi-structured and unstructured data that have the potential to be extracted for information. Examples of Big Data applications in hospitals are expert systems for support in diagnosis and genetic analysis.

*Cloud Computing* is a general term to name anything that has to do with the provision of services and data storage over the Internet. Some examples are hospital administration and management systems, electronic records in the cloud, and backup of biomedical images in the cloud.

*Machine/Deep Learning* is a scientific discipline in the field of Artificial Intelligence that creates systems that learn automatically; learning in this context means identifying types of complex patterns in millions of data more concretely. Deep Learning is one of the learning methods of artificial intelligence, and today belongs to a subfield of Machine Learning. Examples of the use of Machine/Deep Learning in hospitals are automatic diagnosis of radiological images and studies to determine genetic problems.

*Augmented Reality (AR)* is a type of technology that allows to project digital information in the existing environment including the users' vision area, allowing to see part of the real world and graphic information at the same time.

*Virtual Reality (VR):* Similar to AR, it allows visualizing digital images, only that it completely replaces the vision of the real world by covering the entire field of vision. Examples include devices for generating real-time skin surface vasculature maps, 3D visualization of the human anatomy, and surgery planning using advanced surgical navigation platforms (SNAP).

*Remote Control or Monitoring:* Remote patient monitoring (RPM) is a technology that enables monitoring patients outside of common medical sites and includes alerts on a communication device for abnormal readings.

## Appendix B – Standardized residual plot