Effects of contingencies on Healthcare 4.0 technologies adoption and barriers in emerging economies [1]

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Abstract

Studies on the influence of contingency factors on the introduction of novel digital technologies into high-complexity systems, such as hospitals, are still incipient. As the introduction of Healthcare 4.0 (H4.0) usually implies in high capital expenditures and requires a more skilled labor force, such understanding gains relevance when considering hospitals in emerging economies, more likely to be resource-constrained. This study examines the effect of five contingency factors on the adoption of H4.0 technologies and associated barriers to H4.0 adoption in emerging economies; they are: hospital's ownership and age, number of employees, number of inpatient beds, and functionality (teaching hospital or not). The analysis is based on a transnational survey with 159 middle and senior managers from 16 hospitals, located in Brazil, India, Mexico and Argentina. Results indicate that contingencies do affect both H4.0 technologies adoption and associated barriers although not homogeneously in terms of effect, being more prominent on technologies' adoption than on barriers to H4.0 implementation. Our study sheds light on these relationships, providing hospitals' managers a means to anticipate potential issues and handle eventual difficulties inherent to the context in which they are inserted.

Keywords: Healthcare 4.0, Contingency factors, Digital technologies, Barriers, Survey.

1. Introduction

Demands for improvement in healthcare systems have significantly increased over the past few decades. As life expectancy grows and the population becomes older (WHO, 2015) costs associated with health will increase, requiring new approaches to deliver care. Such issue becomes more relevant when considering healthcare systems in emerging economies, where financial and human resources are generally scarcer (Visconti et al., 2017); that may restrict access to high-quality healthcare to a small percentage of the population (Bedir, 2016), negatively impacting the quality of life. Although some emerging economies such as China, Vietnam, India, Colombia and Mexico have recently reformed their health systems to promote universal access and increase quality of healthcare, practical and societal implications are still unknown (Han, 2012), reinforcing the need for developing disruptive approaches to healthcare delivery.

The Fourth Industrial Revolution, also known as Industry 4.0 (I4.0), has raised new opportunities and means for organizations to achieve superior performance levels (Liao et al., 2017). I4.0 denotes the trend of incorporating new digital technologies in production systems (e.g. Internet of Things – IoT, Big data and Cloud computing) such that the virtual space becomes integrated with the physical world (Xu et al., 2018). That integration allows higher modularity and customization of products, processes and services, enabling more assertive decisions and effective solutions whose benefits may impact a wide variety of sectors and contexts (Lasi et al., 2014; Dalenogare et al., 2018), from manufacturing and logistics to healthcare (Li, 2018; Guha and Kumar, 2018).

The adoption of I4.0 principles and technologies in healthcare systems has been referred to as Healthcare 4.0 (H4.0) (Thuemmler and Bai, 2017; Kumari et al., 2018). H4.0 enables real-time customization of healthcare facilitating the transition to a patient-centered environment (Alloghani et al., 2018). Analogously to I4.0, H4.0 is a technology-driven approach that requires fundamental changes in organizations in terms of technical and sociocultural aspects (Nair and Dreyfus, 2018). Despite substantial evidence of H4.0 implementation in the literature (e.g., Yang et al., 2015; Hopp and Wang, 2018; Wang et al., 2018), most studies approach it from a narrow perspective or provide findings based solely on conceptual analysis (Lehoux et al., 2017; Aceto et al., 2018). There is a lack of empirical studies holistically analyzing the implementation of H4.0 technologies (Behkami and Daim, 2012); such gap becomes more evident in the context of emerging economies (Ngwenyama and Morawczynski, 2009), where H4.0 adoption may be constrained by resource scarcity. Besides the socioeconomic context in which the healthcare organization is located, other organizational characteristics may affect the feasibility of H4.0 adoption. For instance, since the implementation of novel digital technologies usually requires high levels of capital expenditure and labor expertise (Furukawa et al., 2008; Avgar et al., 2012; Peng et al., 2014), organizational characteristics (i.e., contingencies) aligned with such requirements may be determinant of a successful H4.0 implementation.

Following contingency theory's principles (Sousa and Voss, 2008), understanding the effect of contingency factors on the adoption of H4.0 might help to systematize the incorporation of technologies, mitigating associated barriers. That would allow hospitals' managers and leaders to more assertively implement H4.0 avoiding misguided efforts and capital expenditures, which are especially important in an emerging economy context. Due to the scarcity of studies that investigate the effects of contingencies on H4.0 adoption and barriers in emerging economies (Nguyen et al., 2014), two research questions are proposed:

i. *What is the effect of contingency factors on the implementation of H4.0 technologies in emerging economies? and*

ii. *What is the effect of those factors on the barriers to H4.0 implementation in emerging economies?*

To answer these questions, this study examines the effect of contingency factors on (*i*) the adoption of H4.0 technologies and on (*ii*) the criticality level of associated barriers in emerging economies. For that, we conducted a transnational survey with 159 middle and senior managers from 16 hospitals located in Brazil, India, Mexico and Argentina. The effect of five contingency factors that characterize hospitals was analyzed on the level of adoption of nine H4.0 technologies and on the criticality level of eight barriers associated to them; contingency factors are (*i*) hospital's ownership, (*ii*) age, (*iii*) number of employees, (*iv*) number of inpatient beds and (*v*) hospital functionality. Such factors have been pointed in the literature as influential in hospitals´ operations.

2. Background

Digital technologies have been playing an important role in healthcare organizations since the 1990s, when the term ‘e-health’ was coined (Aceto et al., 2018). More recently, with the introduction of H4.0 in hospitals, the level of interconnectivity and automation has notoriously increased, allowing both patient care and administrative processes to become more efficient (Yang et al., 2015). As digital technologies became affordable, smaller and capable of managing large quantities of data, H4.0 implementation has become more feasible (Prieto González et al., 2016; Ancarani et al., 2016). The increased level of automation and information exchange inherent to H4.0 not only leads to more qualified, faster and cheaper health services (Ayer et al., 2019; Niemelä et al., 2019), but also allows physicians, nurses and other hospital staff to benefit from internal and cross-hospital services more efficiently (Alloghani et al., 2018; Lolich et al., 2019). Thuemmler and Bai (2017) also listed customization of health and real-time care of patients as an additional outcome derived from H4.0 implementation.

Similar to I4.0, there is no consensus on the set of technologies integrating the H4.0 portfolio; however, H4.0 literature recursively list some technologies that improve hospital’s processes and treatments. Authors such as Zhang et al. (2017), Pace et al. (2019) and Munzer et al. (2019) consistently acknowledge their individual roles as enablers of a more effective healthcare organization. From the nine H4.0 technologies listed in Table 1, ‘biomedical/digital sensors’ and ‘cloud computing’ stood out as they were cited in all investigated studies. In opposition, the application of ‘3D printing’ and ‘collaborative robots’ seems to be less frequently quoted in the literature.

Table 1 also lists barriers to an extensive H4.0 implementation (Wolf and Scholze, 2017). Their incidence in organizations vary according to political and economic interests (Hamidi, 2019), organizational demands (Sannino et al., 2019), and requirements from associations (Ali et al., 2018) and partners (Garai et al., 2017). In general, ‘incorporated IT infrastructure’ and ‘difficulties for finding good partners’ were the most frequently cited in the examined works. At the same time, ‘misalignment with the hospital´s strategy’ and ‘poor knowledge about the technologies’ appeared in only two studies. Despite the variation in citation frequencies, all eight barriers were properly evidenced and consistently discussed in the literature, ensuring their representativeness and relevance for H4.0 adoption.

Complementarily, Thuemmler and Bai (2017) expanded indications by Herman et al. (2015) on I4.0, proposing the incorporation of six design principles into H4.0: (*i*) interoperability, (*ii*) virtualization, (*iii*) decentralization, (*iv*) real-time capability, (*v*) service orientation and (*vi*) modularity. The applicability of such principles has been acknowledged in both experimental/applied (e.g. Wan et al., 2018; Alhussein et al., 2018) and empirical (e.g. Bradley et al., 2018; Wang et al., 2018) studies, although not always explicitly.

Table 1 – H4.0 technologies and barriers mentioned in the literature

3. Research hypotheses

Contingency theory states that there is no best way to organize and manage an organization; the optimal course of action is contingent (i.e. dependent) on factors that are internal and external to the organization (Donaldson, 2001). Operations Management research widely used contingency theory, with examples varying from lean production (Shah and Ward, 2003; Netland, 2016), quality management (Sousa and Voss, 2001), product development (Koufteros et al., 2005) and leadership (Tortorella et al., 2018) to healthcare operations (Friedman and Churchill, Jr., 1987; Salge et al., 2013).

Due to the complexity of healthcare systems, contingency analysis should encompass external (e.g. socioeconomic context of the region/country) and internal (e.g. hospital size and differences in processes and departments) factors. Regarding the former, Bedir (2016) suggested that increases in income level may stimulate healthcare expenditures, while Visconti et al. (2017) indicated that healthcare public-private partnerships significantly differ between developed and emerging countries. Albesher (2019) found that evidence of H4.0 technology adoption in hospitals mostly ranged from pilot projects to full-scale implementations in developed economies (e.g., Japan, France, and Sweden). Studies in industry sectors other than healthcare (e.g., Pagliosa et al., 2019; Rossini et al., 2019; Tortorella et al., 2019a) have already indicated that the socioeconomic context characterizing the organization's geographic location affects the implementation level of disruptive digital technologies (e.g., IoT, cloud computing, collaborative robots, and 3D printing).

Overall, studies suggest that contextual differences account for the diversity in H4.0 approaches and obtained results, highlighting the need for a better understanding of the role of contingencies in H4.0 implementation, particularly in emerging economies. Such evidence justifies the development of research focusing on the socioeconomic context so that the influence of external factors could be mitigated, leading to more assertive results and conclusions. This fact has motivated the investigation of H4.0 adoption and barriers in hospitals located in emerging economies, which is addressed in our study.

Research on internal contingency factors is also prolific. Kimberly and Evanisko (1981) examined the impact of number of inpatient beds, employees and total assets on hospitals' ability to innovate. Sjetne et al. (2007) considered variables such as number of inpatient beds and hospital's functionality to determine patients' experiences. Theokary and Ren (2011) complemented by empirically assessing the impact of patient volume and hospital's functionality on the quality of provided services, indicating that as hospitals' teaching activities increase, greater patient volume is associated with decreased process quality. Researchers have also discussed the effect of context on H4.0 implementation, considering some isolated factors. Moores (2012) and Zhang et al. (2017) examined the moderating effect of demographic factors deemed internal contingencies (e.g. gender and age) on the adoption level of new technologies in healthcare systems. Pan et al. (2018) studied behavioral intentions toward smart healthcare services among medical technicians and clinicians, from the perspective of technology transfer.

Studies consistently suggest five internal contingencies as potentially influential in H4.0 implementation; they are: (i) hospital's ownership, (ii) age, (iii) number of employees, (iv) number of inpatient beds, and (v) hospital functionality. In terms of hospital's ownership, public hospitals in emerging economies are more likely to lack resources (e.g., personnel, equipment and infrastructure) than private ones (Daemmrich, 2013; Visconti et al., 2017). Such resource scarcity may impose additional barriers to H4.0, resulting in an organizational context that might negatively influence the implementation level of its associated technologies. Concerning that, we argue that a hospital's ownership (i.e., private or public) might affect the implementation of H4.0 technologies and barriers. Regarding age, since H4.0 adoption may require a more sophisticated IT infrastructure to properly allocate its associated digital technologies (Garai et al., 2017; Zhang et al., 2017; Elhoseny et al., 2018), hospitals with older facilities might potentially present additional difficulties. In opposition, newer hospitals, whose IT infrastructure has been designed and built more recently, may present a more supportive environment for H4.0 technologies adoption. To the best of our knowledge, no empirical evidence about the effect of age on H4.0 adoption and barriers is available in the literature, justifying the analysis of such a factor.

The number of employees and the number of inpatient beds are two different measures that may be used as proxies to indicate the size of hospitals (Kim et al., 2009; Giancotti et al., 2017). Larger hospitals are more likely to be resourceful in terms of personnel and equipment (Burke et al., 2002; Roh et al., 2013). Such hospitals may also display a higher capital expenditure capacity (Kim et al., 2002), which might favor the purchasing and adoption of sophisticated medical and information technologies. These arguments motivated our analysis of the effect of hospital size on H4.0 adoption and barriers. Regarding hospital functionality, most studies divide hospitals in teaching and non-teaching (Grosskopf et al., 2001; Gok and Sezen, 2012; Amarneh, 2017) when analyzing their management approaches. The literature reports contradictory evindence regarding this contingency factor: while some claim that teaching hospitals might benefit from a highly qualified staff (Kupersmith 2005; Harrison et al., 2010) which, up to a certain extent, would increase the feasibility for actually adopting H4.0, others argue that non-teaching hospitals may favor the establishment of a more patient-centered environment (as they do not need to worry with students), which is a key feature of H4.0 (Thuemmler and Bai, 2017; Alloghani et al., 2018).

To verify the effect of the contingency factors discussed above on H4.0 adoption and barriers in hospitals located in emerging economies, we formulated the following hypotheses:

H1a: *Contingency factors may be used to distinguish between hospitals that are high and low adopters of H4.0 technologies in emerging economies*.

H1b: *Contingency factors have a significant effect on the implementation of H4.0 technologies in emerging economies*.

H2a: *Contingency factors may be used to distinguish between hospitals that are highly and lowly constrained by barriers to H4.0 implementation in emerging economies*.

H2b: *Contingency factors have a significant effect on barriers to H4.0 implementation in emerging economies*.

4. Research method

We now present the method in terms of (*i*) sample characteristics and data collection; (*ii*) measures and instrument development, and (*iii*) data analysis, which are detailed in the following sections.

4.1. Sample characteristics and data collection

To examine the effect of contingency factors on H4.0 implementation in emerging economies, we conducted a transnational survey 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. We also aimed at obtaining multiple responses, from middle and senior managers with different backgrounds and roles (clinician and non-clinician), within each hospital to avoid potential issues related to single-respondent bias (Hair et al., 2014). Collecting information from multiple respondents per hospital also improves our study's internal validity and reliability (Brewer and Crano, 2000; Tabachnik and Fidell, 2013). All respondents play key leadership roles in their hospitals, with backgrounds varying from Information Technology and Business Administration to Nursing and Medicine. To mitigate misinterpretations that could potentially lead to erroneous responses we provided a brief explanation on H4.0 and examples of related technologies with the questionnaire, as suggested by Kothari (2004). Finally, all respondents are associated to tertiary care hospitals, with processes and treatments that are similar in terms of complexity.

Data collection took place between May and June 2018, and was carried out by leading researchers from the selected countries who have extensively published on Healthcare Operations Management. That favored their understanding of the research topic and facilitated access to respondents through their networks. We informed in the invitation that participation was voluntary, and that participants would receive a managerial report once the research was finished. The final sample was comprised of 159 responses from 16 hospitals, averaging 9.9 respondents per hospital (see Table 2). Most respondents were located in Brazil (42.1%) and worked in private hospitals (56.0%) with more than 150 inpatient beds (74.8%). Most of them were associated to teaching hospitals (69.8%) with less than 2,000 employees (74.2%), with facilities less than 20 years-old (52.8%). 74.2% of respondents were supervisors or coordinators; 57.2% led clinician departments and 79.9% had more than 2 years of experience in the role. We considered the collected data to satisfactorily represent perceptions across several hospitals with different contextual variables.

Table 2 – Sample characteristics (*n* = 159)

4.2. Measures and instrument development

The questionnaire was divided in three parts. The first consisted of questions to gather information on respondents and their hospitals. Contingency factors investigated were associated with questions presented at two levels to facilitate answers; they are shown in Table 2. Hospital's ownership was categorized as belonging to either private or public organizations. Hospital size was divided in two contingency factors (number of beds and number of employees) both presented at two levels. We used 150 inpatient beds as threshold to categorize small (less or equal to 150) and large (more than 150 inpatient beds) hospitals, following Sjetne et al. (2007)'s classification, and 2,000 employees as threshold to classify hospitals as small (less or equal to 2,000) or large (more than 2,000 employees). Hospital's age was categorized according to IW (2013), which classifies facilities with more than 20 years as old. Finally, respondents indicated whether their hospitals combined assistance to patients with teaching to medical students and nurses supported by a medical/nursing school or university, being or not a teaching hospital.

In the second part respondents were asked about the adoption level of nine H4.0 technologies (displayed in upper half of Table 1) in their hospitals using a five-point scale, ranging from 1 (not used) to 5 (fully adopted). The concept of H4.0 cannot be considered as widespread, and we avoided referring to it explicitly. Instead, we assessed the adoption of technologies as a proxy for H4.0 implementation, mitigating misinterpretations by respondents. Such approach was also used in similar studies on the topic of I4.0 (e.g. Tortorella and Fettermann, 2018).

In the third part we assessed barriers to H4.0 implementation in the respondents' hospitals. The eight barriers shown in the bottom half of Table 1 were measured using a Likert scale, ranging from 1 (not critical) to 5 (highly critical).

The questionnaire design was pre-tested by seven experts to verify its quality: four were experienced researchers in the area of Healthcare Operations Management and three were hospital managers who have previously collaborated with the research group. In general, experts recommended minor adjustments in the taxonomy and the inclusion of a glossary with examples, which was sent together with the questionnaire. We tested responses related to H4.0 technologies and barriers separately for reliability. Cronbach's alpha values for H4.0 technologies and barriers were 0.841 and 0.853, respectively, satisfying Meyers et al.'s (2006) threshold of 0.6 or higher. Table 3 reports pairwise correlations for the variables associated with the 9 technologies and 8 barriers, and their respective means and standard deviations.

We adopted some countermeasures to mitigate common method bias. First, we used different scale anchors to avoid covariation (Podsakoff et al., 2003). A statement emphasizing that there were no right or wrong answers, and that responses would be treated anonymously was added in the first part of the questionnaire to prevent respondent bias. We also performed Harman's single-factor test to check for common method bias (Malhotra et al., 2006). All variables loaded in a first factor that explained 30.5% of the variance, which was similar to results from previous studies that applied this test (Marodin et al., 2016).

Table 3 – Pairwise correlations' matrix, means and standard deviations

4.3. Data analysis

Data analysis was carried out in two main steps. First, we performed cluster analyses for H4.0 technologies and barriers. In both analyses Ward's hierarchical method was initially applied to identify the adequate number (k) of clusters (Rencher, 2002). Next, observations were assigned to one of the k clusters using the k-means method (Gordon, 1999), and an ANOVA was carried out to check for significant differences (p-value < 0.05) in the means of the clustering variables in each cluster, validating them. Clustering of observations was a step necessary to test hypotheses H1a and H2a. Once clusters for H4.0 technologies and barriers were available, we used Pearson's Chi-Squared test (Tabachnick and Fidell, 2013) to check for differences in individuals in clusters regarding the five contingency factors.

Second, we ran a MANOVA (Multivariate Analysis of Variance) using Wilks' lambda test to check for differences in levels of each contingency factor when considering the degree of H4.0 technologies and barriers. That allowed us to test hypotheses H3 and H4. It is important to mention that to verify whether countries' differences affected H4.0 adoption and barriers, we performed a pre-test on our sample. We ran a MANOVA (Multivariate Analysis of Variance) using Wilks' lambda test to check for differences among countries when considering the degree of H4.0 technology implementation and the presence of barriers to H4.0. Results were not statistically significant, i.e., there was no effect of country on responses regarding H4.0 implementation. We thus grouped all responses and treated our sample as representative of the emerging economy socioeconomic context. Ten MANOVA models were then tested, each considering a contingency factor as independent variable and perceptions on H4.0 technologies' adoption and barriers as dependent variables. Box's test for equality of covariance matrices for all MANOVA tests resulted not significant, satisfying the MANOVA model's assumption. That implies in the null hypothesis of equal (dependent variables') covariance matrices across groups not being rejected (Hair et al., 2014). Whenever a MANOVA model displayed a significant *F*-value we ran individual ANOVA tests to better examine differences in the dependent variables.

5. Results

The hierarchical cluster analysis on adoption level of H4.0 technologies pointed to two clusters of respondents. We thus set $k = 2$ in the *k*-means cluster analysis and assigned respondents to clusters, as shown in the upper half of Table 4. The first cluster, labeled "high adopters", comprised 53 respondents displaying higher adoption levels of H4.0 technologies. The second cluster, labeled "low adopters", comprised 106 respondents displaying lower adoption levels of H4.0 technologies. The ANOVA indicated significant differences (p-values < 0.01) in means of adoption levels of all nine H4.0 technologies between the two clusters. These results validate hypothesis H1a that states that contingency factors may be used to distinguish between hospitals that are high and low adopters of H4.0 technologies in emerging economies.

Similarly, the hierarchical cluster analysis on the criticality of H4.0 barriers pointed to two clusters of respondents; parameter k was set to 2 in the *k*-means analysis which assigned respondents to clusters, leading to results in the bottom half of Table 4. Respondents with lower mean criticality values were assigned to the first cluster ($n_1 = 80$), which was labeled "lowly constrained". In opposition, the second cluster ($n_2 = 79$) was comprised of respondents with higher mean criticality values, being labeled "highly constrained". The ANOVA showed that means of all eight barriers differed significantly (p-value < 0.01) between clusters. These results validate hypothesis H2a that states that contingency factors may be used to distinguish between hospitals that are highly and lowly constrained by barriers to H4.0 implementation in emerging economies.

Table 4 – Cluster analysis results for H4.0 technologies (upper half) and barriers (lower half)

We now report results from Pearson's Chi-Squared tests for the contingency factors shown in Table 5. Our findings indicate that three factors are significantly associated with the adoption level of H4.0 technologies. The first one is hospital's age ($\chi^2 = 5.56$; p-value < 0.05). The frequency of high adopters with newer facilities (< 20 years-old) is higher than with older facilities (> 20 years-old); in opposition, the frequency of low adopters with older hospitals is higher than those with newer facilities. Overall, results for this contingency factor suggest that respondents from older hospitals are less likely to adopt H4.0 technologies than those from newer hospital. The second significant contingency factor is number of inpatient beds ($\chi^2 = 4.83$; p-value < 0.05). The frequency of low adopters in large hospitals and high adopters in small hospitals is significantly larger than other combinations of adoption level and hospital size. The third significant contingency factor is teaching hospital ($\chi^2 = 30.22$; p-value < 0.01). There are larger frequencies of high adopters in non-teaching hospitals and of low adopters in teaching hospitals; i.e. hospitals that are exclusively focused on patient care (i.e. non-teaching hospitals) are more likely to be extensively adopting H4.0 technologies while the frequency of teaching hospitals categorized as low adopters is significantly higher than that of high adopters.

As reported in Table 5, a single contingency factor (hospitals' functionality; $\chi^2 = 7.35$; p-value < 0.01) appeared as significantly associated with H4.0 barriers. Leaders in teaching hospitals perceive barriers to H4.0 implementation more intensely (highly constrained); in opposition, barriers are perceived as less important (lowly constrained) by leaders from hospitals that do not combine assistance to people with teaching.

Table 5 – Composition characteristics of clustering according to H4.0 technologies and barriers

We now report results from the MANOVA analyses shown in Table 6. Two tests were run for each contingency factor. Models 1 and 6, for example, were run using contingency factor "hospital's ownership" as independent variable and nine H4.0 technologies (Model 1) and eight H4.0 barriers (Model 6) as dependent variables. All models that used H4.0 technologies as dependent variables were statistically significant, with *p*-values < 0.01, supporting hypothesis H1b; in opposition, only Models 8 (number of employees) and 10 (teaching hospital) were significant among those using H4.0 barriers as dependent variables, partially supporting hypothesis H2b. To better discriminate the effect of contingencies on H4.0 technologies and barriers, whenever a MANOVA test yielded significant result, univariate ANOVA (Analysis of Variance) tests were run for each independent variable. Levene's test did not indicate differences in dependent variables' error variances enabling the use of ANOVA tests.

Table 6 – MANOVAs using Wilks' lambda test

Table 7 gives ANOVA results that enable verifying the effects of significant contingencies on individual H4.0 technologies. Considering the contingency factor "hospital's ownership" as independent variable only the adoption level of *Cloud computing* is significantly different, being predominant in public hospitals. Contingency factor "hospital's age" significantly discriminates the adoption level of four H4.0 technologies (*Biomedical/Digital sensors*, *IoT*, *Big data*, and *Machine/Deep learning*), such that all of them are more predominant in hospitals with newer facilities (< 20 years-old). Contingency factor "number of employees" significantly discriminates the adoption level of three H4.0 technologies (*Collaborative robots*, *IoT* and *Augmented reality/simulation*), such that two of them are more predominant in larger hospitals (more than 2,000 employees. Results are different for contingency factor "number of inpatient beds", another proxy for hospitals size; two H4.0 technologies are significant related to this factor (*Biomedical/Digital sensors* and *IoT*) and are more predominant in smaller hospitals (< 150 inpatient beds). Finally, "teaching hospital" appeared as the most influential contingency factor for implementing H4.0 technologies, displaying a significant effect in eight of them, all of which were more predominant in non-teaching hospitals. The only exception was *3D printing* with adoption levels not significantly different between teaching and non-teaching hospitals.

Table 8 gives ANOVA results for MANOVA models 8 and 10 in Table 6, related to H4.0 barriers. Contingency factor "number of employees" is significantly related to only one barrier (*Regulatory changes*); leaders from larger hospitals (> 2,000 employees) perceive this barrier as less critical than leaders from smaller hospitals (< 2,000 employees). Findings for "teaching hospitals" indicate that this contingency factor is significantly associated with six barriers for H4.0 implementation (*Regulatory changes*, *Misalignment with hospital´s strategy*, *Information security risks*, *Implementing costs*, *Absence of a qualified team* and *Difficulties for finding good partners*), such that all of them appear as more critical in teaching hospitals.

Table 7 – Univariate ANOVAs for H4.0 technologies

Table 8 – Univariate ANOVAs for H4.0 barriers

6. Discussion

Table 9 summarizes our research findings. Results for hospital's ownership indicate that this contingency factor may be used to distinguish between hospitals that are high and low adopters of H4.0 technologies, but cannot be used to distinguish between those that are highly and lowly constrained by barriers to H4.0 implementation in emerging economies. When analyzing ownership effects on the adoption of specific H4.0 technologies in Table 7 new information arise. The level of adoption of *cloud computing* in public hospitals is larger than in private hospitals. Public hospitals play a prominent social role in emerging economies. According to the Brazilian Health Ministry (2015), 71.1% of the population seek care in public hospitals. They are also representative in Mexico, accounting for 71% of the healthcare capacity (Mexican Health Secretary, 2016), and India, where only 5% of visits to health practitioners are in private clinics or hospitals (Hammer et al., 2017). The use of *cloud computing* enables generating healthcare statistics that are usually required by controlling agents auditing public healthcare systems; it also allows information from patients to be available in different stages of the healthcare process, some of which take place outside the hospital. That justifies the predominant adoption of *cloud computing* in public hospitals.

Table 9 – Summary of results

Regarding age, our findings indicate that newer hospitals provide a more suitable environment for implementing H4.0 technologies. Older facilities are often associated with higher difficulty to learn and change (Tortorella et al., 2015), either in technical or sociocultural aspects. The age of a facility is claimed to inversely impact the rate of innovative improvements, since its organizational routines, standards and infrastructure are usually designed and determined in the very early years (Stinchcombe, 1965; Aldrich, 1979; Nelson and Winter, 1982, Shah and Ward, 2003). In this sense, older organizations might find more difficult to incorporate new approaches that significantly modify their current processes, products, structure and services. Since disruptive digital technologies encompassed by H4.0 demand specific information and communication infrastructure (Wolf and Scholze, 2017) and entail relevant rearrangements in the way processes and services are organized in a hospital (Thuemmler and Bai, 2017), it is reasonable to expect that older hospitals present lower H4.0 implementation levels. Our results support this assumption and agree with findings in Lefebvre (2010), who claims that older hospitals struggle to remain competitive. We thus argue that newer hospitals may provide an environment for addressing organizational and structural issues that contribute to the implementation of H4.0 technologies.

Regarding hospital size, different insights are available depending on the proxy used. With respect to number of employees, larger hospitals seem to more extensively adopting H4.0 technologies (e.g. collaborative robots and augmented reality/simulation) and are less constrained by regulatory changes. When considering number of beds as proxy for hospital size, smaller hospitals present a higher adoption level of H4.0 technologies. Previous research suggests that organization size may affect innovation and improvement initiatives both ways. On one hand, larger organizations may benefit from more structured processes and higher levels of resources, both capital and human (Dewar and Dutton, 1986; Schminke et al., 2002; Shah and Ward, 2003; Marodin et al., 2016); on the other hand, they display high complexity and bureaucracy, which may undermine new management approaches (Kalleberg et al., 1996; Amato and Amato, 2007; Laforet, 2013). Our results add to this discussion and suggest that, while hospitals with a larger number of employees may generally benefit from H4.0 implementation due to higher availability of capital and human resources, hospitals with lower number of beds may display a more appropriate environment to H4.0 adoption, with lower complexity and less barriers to innovation in their processes. Such conclusions are aligned with those by Watcharasriroj and Tang (2004), who showed that both large and small hospitals in Thailand appear to be positively affected by information technologies.

Hospital functionality is the most prominent contingency factor in our analysis, significantly impacting both H4.0 technologies and barriers and allowing a clear distinction between hospitals. Teaching hospitals usually demand a more qualified medical staff and openness to learning (Ayanian and Weissman, 2002; Kupersmith 2005). That should increase the level of innovation, while attracting highly skilled employees (physicians, nurses, technicians, etc.). However, according to Theokary and Ren (2011), as teaching intensity increases a larger number of inexperienced students will be inserted into the hospital, resulting in lack of continuity and a seasonal reduction in the expertise level of the workforce [that may explain Sjetne et al.'s (2007) finding that patients from large-sized teaching hospitals are less satisfied in terms of the service provided than patients from large-sized non-teaching hospitals]. Our findings corroborate to Theokary and Ren's (2011) assumption, since they indicate that teaching hospitals present a less favorable environment for H4.0 implementation. In other words, not only the adoption level of technologies is higher in non-teaching hospitals, but also leaders from these hospitals feel less constrained by barriers to H4.0 implementation. Thus, we conclude that this contingency factor highly affects the chances of a successful H4.0 implementation.

Finally, an additional insight derived from our study is worth mentioning. Although we have not aimed to perform any comparative analysis among H4.0 technologies, results displayed in Table 3 suggest that 3D printing, collaborative robots, machine/deep learning and augmented reality/simulation might present lower mean adoption levels (with means varying from 1.408 to 1.704) than the remaining technologies (with means varying from 2.144 to 2.968) in hospitals located in emerging economies. This trend was also observed in Tortorella et al. (2019b), who noted that these digital technologies were less frequently cited in the literature. This fact may indicate that, depending on the set of digital technologies considered, there are different levels of maturity within hospitals in emerging economies. In this sense, the extent of the effect of contingencies on the adoption level of H4.0 technologies might be affected by their readiness level. In other words, H4.0 technologies with lower readiness levels (represented by their mean adoption level as proxy) may be less sensitive to the effect of contingencies. However, our study does not provide enough data to fully support this claim, which may be viewed as a possible extension of the current research.

7. Conclusions

7.1. Implications to theory

Our study contributes to theory related to healthcare operations management in different ways. H4.0 is a recent concept and the body of knowledge on its implementation is still incipient. Our findings shed light on the effect of contingencies in H4.0 implementation, both in terms of related technologies' adoption level and barriers to their implementation in emerging economies. Aligned with the contingency theory, we found that different environments require different managerial actions to enable H4.0 adoption. Moreover, despite economic and social constraints in emerging economies, our findings point to several levels of H4.0 technology adoption in hospitals from those countries. That somewhat demystifies the assumption that the integration of new digital technologies arising from I4.0 into healthcare organizations may be impaired by socioeconomic constraints. In fact, our research shows that the effect of contingencies on barriers to H4.0 implementation is less pervasive than expected, with only two of the investigated contingency factors being significantly associated with those barriers. In opposition, when exclusively considering the adoption level of H4.0 technologies, contingencies play a more relevant and intriguing role, with some associations appearing as counterintuitive in light of previous literature (e.g. the effect of hospital's ownership). That may be justified by specificities of the socioeconomic context in which this study was carried out, adding insightful implications to theory. As far as our knowledge goes, we are not aware of any similar study in the literature.

7.2. Implications to practice

With respect to practical contributions, this research provides healthcare practitioners and leaders statistical evidence on contingencies that may impact their initiatives towards H4.0 implementation; as hospitals are complex sociotechnical systems with different contextual characteristics, our findings support managers to take more assertive actions. The identification of H4.0 technologies that are more likely to be extensively adopted in each context allows the prioritization of managerial efforts, enabling the achievement of expected benefits in the short term. Further, by comprehending the context in which their hospitals are inserted practitioners may be able anticipate potential issues and address countermeasures to mitigate barriers to H4.0 implementation. That is particularly relevant to leaders aiming at implementing H4.0 in teaching hospitals, which are more susceptible to present significant barriers. Finally, this investigation provides governments and health institutions/associations from emerging economies arguments to aid the development of strategic initiatives and foster the improvement of their healthcare systems, increasing productivity and quality levels. This is a key practical implication not only to hospitals but also to society, since it enhances healthcare systems by truly inserting them into the Fourth Industrial revolution era.

7.3. Limitations and future research

A few limitations of this research are worth mentioning. First, we assessed the individual effect of each contingency factor on H4.0 technologies and barriers. Although we followed a methodological approach applied in studies with similar objectives (e.g. Netland, 2016; Marodin et al., 2016), we understand that interaction effects between contingencies may raise additional insights. The relevance of such interaction effects was pointed out by Damanpour (1992) and Theokary and Ren (2011), and is a limitation of our study and an opportunity for future research. Second, our findings are restricted to the context of emerging economies. Further research could expand the dataset to include respondents in developed economies, allowing further comparisons.

Due to our study's purpose, we did not assess the existence of relationships between H4.0 technologies and barriers or examined their effects on hospitals' operational performance. Additional studies could be designed to provide empirical evidence on such relationships. Our results brought attention to sets of technologies with different readiness levels within hospitals located in emerging economies. In this sense, future research could accurately identify these sets of technologies and verify how their readiness levels influence the effects of contingencies on H4.0 adoption and barriers.

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Tables

Table 1 –H4.0 technologies and barriers mentioned in the literature

		Garai et al. (2017)	Zhang et al. (2017)	Elhoseny et al. (2018)	Ali et al. (2018)	Pace et al. (2019)	Munzer et al. (2019)	Hamidi (2019)	Sannino et al. (2019)	Frequency (%)
H4.0 technologies	Biomedical/Digital sensors	√	√	√	√	√	√	√	√	100.0%
	3D printing		√							12.5%
	Collaborative robots		√							12.5%
	IoT	√	√	√		√	√	√	√	87.5%
	Big data		√	√		√		√	√	62.5%
	Cloud computing	√	√	√	√	√	√	√	√	100.0%
	Machine/Deep learning		√	√				√		37.5%
	Augmented reality/simulation		√				√			25.0%
	Remote control or monitoring		√			√	√	√		50.0%
H4.0 barriers	Regulatory changes		√		√			√		37.5%
	Incorporated IT infrastructure	√	√	√	√	√	√	√		87.5%
	Misalignment with hospital´s strategy							√	√	25.0%
	Information security risks	√	√		√	√			√	62.5%
	Implementing costs		√		√	√	√	√		62.5%
	Poor knowledge about the technologies		√		√					25.0%
	Absence of a qualified team		√			√	√			37.5%
	Difficulties for finding good partners	√	√		√	√	√	√	√	87.5%

Table 2 – Sample characteristics (*n* = 159)

Country			Number of inpatient beds			Respondent's experience		
Brazil	67	42.1%	Less than 150	40	25.2%	Less than 2 years	32	20.1%
India	36	22.6%	More than 150	119	74.8%	More than 2 years	127	79.9%
Mexico	34	21.4%	**Hospital's age**			**Respondent's role**		
Argentina	22	13.8%	Less than 20 years-old	84	52.8%	Supervisor or Coordinator	118	74.2%
Number of employees			More than 20 years-old	75	47.2%	Manager or Director	41	25.8%
Less than 2,000	118	74.2%	**Hospital's ownership**			**Respondent's department**		
More than 2,000	41	25.8%	Public	70	44.0%	Non-clinician	68	42.8%
Teaching Hospital			Private	89	56.0%	Clinician	91	57.2%
No	48	30.2%						
Yes	111	69.8%						

Table 3 – Pairwise correlations' matrix, means and standard deviations

Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1-Biomedical/Digital sensors	2.968	1.366	-	0.156**	0.129	0.438***	0.379***	0.374***	0.293***	0.196**	0.201**	0.086	0.163**	0.093	0.115	0.083	0.021	-0.019	-0.094
2-3D printing	1.559	1.034		-	0.313***	0.084	0.114	0.139	0.268***	0.340***	0.094	0.029	-0.037	-0.007	-0.080	0.035	-0.065	-0.011	-0.043
3-Collaborative robots	1.408	1.007			-	0.250***	0.333***	0.231***	0.559***	0.609***	0.455***	0.174**	0.114	0.209***	0.198**	0.153	0.110	0.138	0.081
4-IoT	2.673	1.536				-	0.404***	0.320***	0.337***	0.250***	0.396***	0.059	0.108	0.063	0.092	0.093	0.135	0.093	0.059
5-Big data	2.125	1.390					-	0.448***	0.480***	0.320***	0.506***	0.294***	0.175**	0.306***	0.351***	0.247***	0.100	0.209***	0.232***
6-Cloud computing	2.647	1.463						-	0.407***	0.200**	0.378***	0.160**	0.152	0.194**	0.155	0.135	-0.001	0.047	0.025
7-Machine/Deep learning	1.704	1.193							-	0.430***	0.527***	0.221***	-0.033	0.097	0.068	0.208***	-0.015	-0.016	-0.013
8-Augmented reality/simulation	1.635	1.069								-	0.369***	0.174**	0.090	0.198**	0.264***	0.151	0.178**	0.169**	0.125
9-Remote control or monitoring	2.144	1.306									-	0.191**	0.081	0.252***	0.237***	0.247***	0.080	0.096	0.166**
10-Regulatory changes	2.911	1.218										-	0.380***	0.376***	0.434***	0.223***	0.265***	0.316***	0.328***
11-Incorporated IT infrastructure	2.842	1.172											-	0.431***	0.425***	0.380***	0.324***	0.393***	0.322***
12-Misalignment with hospital´s strategy	2.880	1.165												-	0.562***	0.236***	0.571***	0.474***	0.508***
13-Information security risks	2.911	1.229													-	0.370***	0.449***	0.450***	0.465***
14-Implementing costs	2.540	1.385														-	0.356***	0.429***	0.253***
15-Poor knowledge about the technologies	2.924	1.250															-	0.678***	0.564***
16-Absence of a qualified team	2.767	1.278																-	0.608***
17-Difficulties for finding good partners	2.981	1.182																	-

Notes: $^{**}p$-value < 0.05; $^{***}p$-value < 0.01.

Table 4 – Cluster analysis results for H4.0 technologies (upper half) and barriers (lower half)

H4.0 technologies	Clusters means		F-value
	High adopters (n_1 = 53)	Low adopters (n_2 = 106)	
Biomedical/Digital sensors	3.89	2.51	46.20***
3D printing	1.94	1.37	11.67***
Collaborative robots	1.98	1.12	30.42***
IoT	3.85	2.08	65.64***
Big data	3.32	1.53	92.85***
Cloud computing	3.91	2.02	92.94***
Machine/Deep learning	2.79	1.16	112.80***
Augmented reality/simulation	2.21	1.35	26.41***
Remote control or monitoring	3.15	1.64	66.81***
H4.0 barriers	Clusters means		F-value
	Lowly constrained (n_1 = 80)	Highly constrained (n_1 = 79)	
Regulatory changes	3.40	2.42	30.66***
Incorporated IT infrastructure	3.46	2.22	62.54***
Misalignment with hospital´s strategy	3.50	2.25	63.43***
Information security risks	3.64	2.18	86.41***
Implementing costs	3.16	1.91	40.49***
Poor knowledge about the technologies	3.70	2.14	101.16***
Absence of a qualified team	3.59	1.94	113.32***
Difficulties for finding good partners	3.66	2.29	80.28***

Notes: $^{*}p$-value < 0.10; $^{**}p$-value < 0.05; $^{***}p$-value < 0.01.

Table 5 – Composition characteristics of clustering according to H4.0 technologies and barriers

Contingency factors		Technologies				
		High adopters		Low adopters		Test
Hospital's ownership	Public or Mixed	24	34.3%	46	65.7%	Pearson's $\chi^2 = 0.05$
	Private	29	32.6%	60	67.4%	
Hospital's age	< 20 years-old	35	41.7%	49	58.3%	Pearson's $\chi^2 = 5.56^{*}$
	> 20 years-old	18	24.0%	57	76.0%	
Number of employees	< 2,000 employees	40	33.9%	78	66.1%	Pearson's $\chi^2 = 0.07$
	> 2,000 employees	13	31.7%	28	68.3%	
Number of inpatient beds	< 150 beds	19	47.5%	21	52.5%	Pearson's $\chi^2 = 4.83^{*}$
	> 150 beds	34	28.6%	85	71.4%	
Teaching Hospital	No	31	64.6%	17	35.4%	Pearson's $\chi^2 = 30.22^{**}$
	Yes	22	19.8%	89	80.2%	
Contingency factors		Barriers				
		Lowly constrained		Highly constrained		Test
Hospital's ownership	Public or Mixed	33	47.1%	37	52.9%	Pearson's $\chi^2 = 0.50$
	Private	47	52.8%	42	47.2%	
Hospital's age	< 20 years-old	44	52.4%	40	47.6%	Pearson's $\chi^2 = 0.30$
	> 20 years-old	36	48.0%	39	52.0%	
Number of employees	< 2,000 employees	61	51.7%	57	48.3%	Pearson's $\chi^2 = 0.35$
	> 2,000 employees	19	46.3%	22	53.7%	
Number of inpatient beds	< 150 beds	21	52.5%	19	47.5%	Pearson's $\chi^2 = 0.10$
	> 150 beds	59	49.6%	60	50.4%	
Teaching Hospital	No	32	66.7%	16	33.3%	Pearson's $\chi^2 = 7.35^{**}$
	Yes	48	43.2%	63	56.8%	

Notes: $^{*}p$-value < 0.05; $^{**}p$-value < 0.01

Table 6 – MANOVAs using Wilks' lambda test

Effect	H4.0 technologies		Effect	H4.0 barriers	
	Value	*F*		Value	*F*
Model 1 – Hospital's ownership	0.863	2.64^{**}	Model 6 – Hospital's ownership	0.961	0.75
Model 2 – Hospital's age	0.734	5.99^{**}	Model 7 – Hospital's age	0.963	0.72
Model 3 – Number of employees	0.824	3.55^{**}	Model 8 – Number of employees	0.903	2.00^{*}
Model 4 – Number of beds	0.840	3.16^{**}	Model 9 – Number of beds	0.933	1.35
Model 5 – Teaching hospital	0.601	10.99^{**}	Model 10 – Teaching hospital	0.877	2.64^{**}

Notes: $^{*}p$-value < 0.05; $^{**}p$-value < 0.01

Table 7 – Univariate ANOVAs for H4.0 technologies

H4.0 technologies	Ownership		*F*-value	Hospital's age		*F*-value	Nº of employees		*F*-value	Nº of beds		*F*-value	Teaching hospital		*F*-value
	Public	Private		< 20 years-old	> 20 years-old		< 2,000	> 2,000		< 150	> 150		No	Yes	
Biomedical/Digital sensors	3.17	2.81	2.79	**3.38**	**2.51**	17.97**	3.07	2.68	2.44	**3.63**	**2.75**	13.30**	**3.67**	**2.67**	20.13**
3D printing	1.51	1.60	0.24	1.67	1.44	1.91	1.47	1.83	3.82	1.80	1.48	2.92	1.71	1.50	1.42
Collaborative robots	1.34	1.46	0.53	1.31	1.52	1.73	**1.24**	**1.90**	14.38***	1.45	1.39	0.09	**1.83**	**1.23**	13.14**
IoT	2.81	2.56	1.06	**3.02**	**2.28**	9.80**	**2.81**	**2.29**	3.44*	**3.53**	**2.39**	18.23**	**3.37**	**2.37**	15.69**
Big data	1.94	2.27	2.18	**2.48**	**1.73**	12.10**	2.07	2.29	0.80	2.27	2.08	0.61	**3.19**	**1.67**	53.37**
Cloud computing	**2.96**	**2.40**	5.76*	2.67	2.63	0.03	2.61	2.76	0.30	2.95	2.55	2.30	**3.10**	**2.45**	6.94**
Machine/Deep learning	1.69	1.72	0.03	**1.88**	**1.51**	3.97*	1.69	1.76	0.10	1.92	1.63	1.84	**2.56**	**1.33**	45.55**
Augmented reality/simulation	1.60	1.66	0.14	1.77	1.48	3.03	**1.53**	**1.95**	4.94**	1.77	1.59	0.91	**2.10**	**1.43**	14.32**
Remote control or monitoring	1.94	2.30	3.02	2.25	2.03	1.16	2.09	2.29	0.71	2.20	2.13	0.10	**3.10**	**1.73**	48.16**

Notes: **p*-value < 0.05; ***p*-value < 0.01

Table 8 – Univariate ANOVAs for H4.0 barriers

H4.0 barriers	Nº of employees		*F*-value	Teaching hospital		*F*-value
	< 2,000	> 2,000		No	Yes	
Regulatory changes	**2.76**	**3.34**	7.12**	**3.23**	**2.77**	4.77*
Incorporated IT infrastructure	2.86	2.78	0.16	3.02	2.77	1.59
Misalignment with hospital´s strategy	2.83	3.02	0.84	**3.17**	**2.76**	4.23*
Information security risks	2.90	2.95	0.06	**3.42**	**2.69**	12.43**
Implementing costs	2.61	2.34	1.15	**3.10**	**2.30**	12.16**
Poor knowledge about the technologies	2.92	2.95	0.03	3.15	2.83	2.17
Absence of a qualified team	2.73	2.88	0.41	**3.10**	**2.62**	4.89*
Difficulties for finding good partners	3.02	2.88	0.42	**3.31**	**2.84**	5.55*

Notes: **p*-value 0.05; ***p*-value < 0.01

Table 9 – Summary of results

		Contingency factor				
		Hospital's ownership	Age	Nº of employees	Nº of inpatient beds	Hospital functionality
Adoption level of H4.0 technologies	Biomedical/Digital sensors		Newer > Older	-	Smaller > Larger	Non-teaching > Teaching
	3D printing		-		-	-
	Collaborative robots	-		Smaller < Larger		
	IoT		Newer > Older	Smaller > Larger	Smaller > Larger	
	Big data					
	Cloud computing	Public > Private	-	-		Non-teaching > Teaching
	Machine/Deep learning		Newer > Older		-	
	Augmented reality/simulation	-	-	Smaller < Larger		
	Remote control or monitoring			-		
Criticality level of H4.0 barriers	Regulatory changes			Smaller > Larger		Non-teaching < Teaching
	Incorporated IT infrastructure					-
	Misalignment with hospital´s strategy	-	-		-	
	Information security risks			-		Non-teaching < Teaching
	Implementing costs					
	Poor knowledge about the technologies					-

	Absence of a qualified team		Non-teaching < Teaching
	Difficulties for finding good partners		

Note: Empty cells indicate differences that were not statistically significant and, hence, disregarded.