Measuring the effect of Healthcare 4.0 implementation on hospitals' performance

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Abstract

In this study we identify bundles of technologies and associated implementation barriers that could be viewed as part of Healthcare 4.0 (H4.0) and test their impact on performance improvement in a sample of hospitals. For that, we carried out a cross-sectional study with 181 leaders from hospitals in different countries that have already started H4.0 implementation. The collected data was analyzed using multivariate statistical techniques. Results indicate that H4.0 technologies could be organized into two different bundles according to their role within the hospital. Common barriers to H4.0 implementation were also empirically organized in two groups, following the sociotechnical systems theory. Bundles of H4.0 technologies presented a positive and significant effect on hospitals' performance. As their interaction with H4.0 barriers displayed a significant effect on performance improvement, it is important to concurrently consider H4.0 technologies and barriers. Our results allow hospital managers to anticipate potential issues in H4.0 implementation, enabling more assertive efforts to improve performance and deliver high-quality and low-cost care in the fourth industrial revolution era.

Keywords: Healthcare 4.0, Hospital performance improvement, Technologies, Barriers.

1. Introduction

The Fourth Industrial Revolution, also known as Industry 4.0 (I4.0), refers to the trend towards automation and data exchange in industry, supported by modern digital technologies such as Internet of Things (IoT), Cloud Computing, Machine Learning and Big Data (Lasi et al., 2014;

Fatorachian and Kazemi, 2018). Four main design principles are argued to guide I4.0 implementation: interconnection, information transparency, technical assistance and decentralized decisions (Hermann et al., 2016). Such digital transformation has generated high expectations due to the possibilities of developing innovative products, services and processes that may positively impact organizations (Dalenogare et al., 2018), supply chains (Fatorachian and Kazemi, 2020), communities (Lu, 2017) and society (Bauer et al., 2015). Increasing literature evidence has become available on conceptual (e.g. Liao et al., 2017; Xu et al., 2018) and applied research (e.g. Cheng et al., 2016; Thoben et al., 2017) related to I4.0, both in the private sector (e.g. PWC, 2019; Cannon Group, 2019) and in governmental entities (e.g. Brazilian National Confederation of Industry, 2016; Mexican Ministry of Economy, 2016).

Despite the increasing academic and managerial interest in I4.0, much still needs to be investigated to enable its technologies' extensive adoption in different contexts (Bibby and Dehe, 2018). Such gap is observed when considering the digital transformation of healthcare organizations. The adaptation of I4.0 technologies and principles to healthcare systems has been named Healthcare 4.0 (H4.0) (Thuemmler and Bai, 2017; Sannino et al., 2018). H4.0 allows real-time healthcare customization, shifting from hospital-centered to patient-centered organizations in which different departments are synergistically related to provide the best patient health outcome (Alloghani et al., 2018). H4.0 efficiently enables hospital staff to share and benefit from internal and cross-hospital services. Initiatives on H4.0 implementation have been reported mostly in health treatments (e.g. Ciuti et al., 2016; Wolf and Scholze, 2017) and hospital supporting processes (e.g. Alharbi et al., 2016; Ali et al., 2018); while the adoption of new technologies in health treatments may positively impact hospitals' outputs in the short run, the benefits of their integration in administrative/supporting processes may only become apparent in the long term (Das et al., 2011).

There is still no common ground in the literature regarding technologies to be considered in H4.0 implementation (Yang et al., 2015) and how they may interact to improve performance in healthcare systems (Agha, 2014). Similarly, consensus has not yet been reached regarding the exact contribution of H4.0 technologies to hospitals' performance (Bardhan and Thouin, 2013). Results derived from healthcare digital transformation are diverse (Gastaldi and Corso, 2012; Fosso Wamba and Ngai, 2015), especially when considering the influence of barriers related to political and economic interests, and demands from organizations, associations and lobbyists (Wolf and Scholze, 2017). Four research questions arise from the arguments above:

RQ_1. *What are the fundamental bundles of both digital technologies associated with H4.0?*

RQ_2. *What are the fundamental barriers for adopting H4.0?*

RQ_3. *What is the relationship between H4.0 technologies and hospitals' performance?*

RQ_4. *What is the effect of the interaction between H4.0 technologies and barriers on hospitals' performance?*

To answer these questions, we carried out a cross-sectional study with 181 leaders from hospitals located in different countries that have already started H4.0 implementation. Collected data was analyzed using multivariate statistical techniques. We also identified bundles of technologies and associated barriers that should be deemed part of H4.0, adding to the existing propositions on the subject (e.g. Aceto et al., 2018; Guha and Kumar, 2018). We finally tested the effect of interactions between H4.0 technologies and barriers on hospitals' performance.

Our research is grounded on the theory of sociotechnical systems (Cooper and Foster, 1971; Cecconi, 2016) according to which organizational development is achieved through the proper interaction between social and technical aspects of an organization, leading to performance improvements. Sociotechnical systems in organizational development is an approach to complex organizational work design that recognizes the interaction between people and technology in workplaces (Walker et al., 2008). Since we aim at examining H4.0 considering both social and technical aspects implicit to its implementation, our work potentially contributes to those related to the incorporation of novel digital technologies in healthcare organizations.following

The rest of our article is structured as follows. Section 2 discusses the relevant literature to derive the hypotheses for the study. Section 3 presents the methodology adopted by discussing sample selection, development of data collection instrument and measures, verification of constructs' validity and reliability and the analysis of data collected. Section 4 presents the results obtained and links the findings to the hypotheses. Finally, section 5 closes the paper discussing implications of our findings to the state-of-the-art and practice on H4.0 bundles and hospital performance improvement, as well as limitations leading to future research.

2. Literature and hypotheses

I4.0 is the ongoing transformation of traditional manufacturing and industrial practices combined with the latest smart technologies (Fatorachian and Kazemi, 2018). I4.0 focuses on the use of large-scale interconnectivity technology deployments to provide increased automation, improved communication and self-monitoring, as well as smart machines able to analyze and diagnose issues without the need of human intervention (Schroeder et al., 2019). Coined in the 2011 Hannover Fair, the term I4.0 refers to a strong customization of products under the conditions of highly flexible production (Sony and Naik, 2020). The incorporation of I4.0's technologies and design principles into healthcare originated the concept of H4.0 (Thuemmler and Bai, 2017; Sannino et al., 2018). The H4.0 approach is driven by digital technology adoption, requiring vital changes in healthcare organizations in both technical and social aspects (Nair and Dreyfus, 2018; Tortorella et al., 2020a). H4.0's introduction has raised the level of interconnectivity and automation in hospitals, enabling both patient care and administrative processes to become more effective (Yang et al., 2015).

Several studies point to interrelated technologies that can be described as part of the H4.0 implementation portfolio. Baker et al. (2017) list the Internet of Things (IoT), Cloud Computing, Wearable Biomedical Sensors and Machine Learning as enablers of a smart health model. Sakr and Elgammal (2016) adds Big Data Analytics into the H4.0 portfolio. Other researchers explored the individual application of technologies in healthcare systems, such as 3D Printing (Zhang et al., 2017), Collaborative Robots (Dautov et al., 2019), Augmented Reality (Munzer et al., 2019) and Remote Monitoring (Pace et al., 2019). Table 1 consolidates the most commonly cited H4.0 technologies in the literature. Despite variation in citation frequencies, literature evidence suggests that these technologies present complementary roles (Gómez and Carnero, 2011).

Studies proposed distinct bundles (or groupings) of H4.0 technologies. Sharma et al. (2016) categorized technologies into three bundles according to their extent of patient centered integration and caregiver interaction. Aceto et al. (2018) conceptually proposed four overlapped groups of technologies based on their roles and applicability within the hospital. Another categorization of H4.0 technologies is found in Gastaldi and Corso (2012), who proposed four macro-areas subdivided in fourteen solutions provided by each technology. Finally, Alrige and Chatterjee (2015) suggested a taxonomy to classify wearable technologies in healthcare systems according to three major dimensions: application, form and functionality. It becomes clear that a consensus is yet to be reached on what are the bundles of H4.0 technologies and how they could be combined to act synergistically.

Regarding barriers against a successful H4.0 implementation, a similar situation is found in the literature. As in any transfer of knowledge and technology, it seems unlikely that specific practices could be adapted to other environments with equal success (Jimmerson et al., 2005). Literature states that previous technology transfers from an area (e.g. manufacturing) to a new environment (e.g. healthcare sector) present different implementation barriers. For example, lean healthcare adoption was constrained by methodological barriers to early implementation (Vest and Gamm 2009; Curatolo et al., 2013), poor understanding of organizational context (Fournier and Jobin, 2018), lack of monitoring and control (Tlapa et al., 2020), insufficient space and time for team collaborative improvement activities (New et al., 2016), incomplete or slow adoption of practices (Moo-Young et al., 2019), and lack of standardization (Gayed et al., 2013). In addition, some hospitals experienced "project fatigue", which is caused by simultaneous occurrence of multiple problems that deserve attention and tend to disperse efforts (Chassin and Loeb, 2013). Indeed, organizations should minimize the impact of such barriers and capitalize on facilitating conditions that are specific to their contexts (Mazzocato et al., 2012).

Although certain barriers are frequently mentioned (see Table 1), their nature may vary from purely technical difficulties (e.g. incorporated IT infrastructure) to social and organizational challenges (e.g. misalignment with hospital's strategy) (García-Villarreal et al., 2019). Some authors (e.g. Gastaldi and Corso, 2012; Chong et al., 2015; Wolf and Scholze, 2017) state that as the implementation advances additional barriers may emerge, especially if hospitals do not address the required technical and social requirements for H4.0 adoption. Other kinds of barriers related to labor resistance may also be found when adopting new technologies, as emphasized by Pan et al. (2018). Resistance to change is an underlying barrier common in most organizations resulting from reasons that vary across organizational contexts (Lawson and Price, 2003; Simms, 2005), and may be viewed as resulting from the concurrent effects of different variables. Although not included explicitly in our study, we understand that Table 1 exposes eight barriers that can be seen as potential triggers for resistance to change.

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

The extensive integration of new digital technologies into healthcare organizations has been associated with new opportunities and applications that lead to higher performance levels (Guillén et al., 2016; Aceto et al., 2018; Sony and Naik, 2020). Apart the envisioned operational performance improvements, benefits in hospitals' interactions with patients and stakeholders are also claimed (Dent and Pahor, 2015; Wang et al., 2018a). Nevertheless, implications of H4.0 adoption still need to be better investigated (Bardhan and Thouin, 2013; Agha, 2014; Schroeder et al., 2019; Tortorella et al., 2020a).

Some conceptual studies (e.g. Demirkan, 2013; Yuehong et al., 2016; Munzer et al., 2019) suggest a positive association between H4.0 adoption and hospital performance but lack empirical evidence that supports it. The need for empirical studies increases given that the adoption of H4.0 technologies implies the organizational development of not one, but a set of routines. As the number of routines increases, implementation becomes more challenging since developing routines in face of technological changes (i.e. higher-level organizational routines) requires dynamic capabilities (Schilke, 2014). In essence, dynamic capabilities allow firms to capture change opportunities by rearranging resources (Salvato and Vassolo, 2018); however, they are path-dependent and premised on local learning (Levitt and March, 1988; Winter, 2008) such as the ones required by H4.0 technologies.

Applied studies (e.g. Saxena and Raychoudhury, 2017; Alhussein et al., 2018; Wang et al., 2018b) have also reported positive outcomes from the integration of specific H4.0 technologies into medical treatments or administrative processes. However, such studies are usually carried out under a narrow and not generalizable perspective. On the other hand, empirical research that aims at identifying the relationship between H4.0 implementation and hospitals' performance is scarce. Few works, such as the ones conducted by Sharma et al. (2016) and Williams et al. (2016), attempted to examine how technology adoption influenced on hospitals' performance; however, the set of technologies included in those studies were not necessarily listed in the H4.0 portfolio.

As seen above, the body of knowledge on H4.0 implementation presents a theoretical gap regarding empirical examination. One should also consider the organizational barriers against H4.0 implementation and how they compromise the integration of digital technologies into healthcare systems to achieve superior performance results. Particularly noteworthy is the fact that, as the number of technologies increases, organizational resistance will emerge from different groups (Heifetz et al., 2009; Hall et al., 2018) reducing the likelihood of a successful implementation. Following sociotechnical systems theory, the interaction between complex infrastructures and human behavior may affect performance results (Cooper and Foster, 1971). Such interaction consists partly of linear "cause and effect" relationships (i.e. relationships that are usually designed) and partly from non-linear, complex, even unpredictable relationships (i.e. the good or bad relationships that are often unexpected) (Long, 2018). If the interaction is not properly managed, the optimization of each aspect alone might increase not only the number of unpredictable relationships, but also those relationships likely to jeopardize the system's performance (Sovacool and Hess, 2017). With that in view, it becomes relevant to understand how the interaction between social and technical aspects of H4.0 implementation create conditions to achieve a superior hospital performance. To better verify these associations, we formulate the following hypotheses:

H1. *The adoption of H4.0 technologies is positively associated with hospitals' performance improvement.*

H2. *The interaction effects between the adoption level of H4.0 technologies and the constraining level of barriers are negatively associated with hospitals' performance improvement.*

3. Method

Due to its exploratory nature, the methodological procedure of this research followed an empirical approach. Goodwin (2005) recommended empirical research as a way of gaining knowledge by means of direct/indirect observation or experience. Quantifying empirical evidence collected from non-random respondents that meet certain criteria is a common approach in similar studies (e.g. Marodin et al., 2018), and can help answering the aforementioned research questions. Among the existing methods of data gathering for empirical research purposes, the survey method is frequently adopted due to its various advantages, such as high level of representativeness, low cost, potential statistical significance and standardized stimulus to all respondents (Montgomery, 2013). The method proposed in this paper consists of four main steps (see Figure 1): (*i*) sample selection and characterization; (*ii*) development of data collection instrument and measures; (*iii*) verification of constructs' validity and reliability; and (*iv*) data analysis. The subsequent sections provide detailed information on these steps.

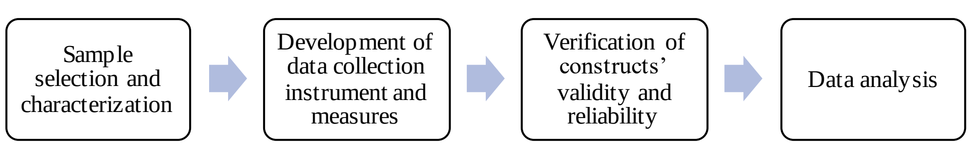

Figure 1 – Proposed research steps

3.1. Sample selection and characterization

We carried out a transnational survey with hospitals from six countries: Argentina, Brazil, India, Italy, Mexico, and USA. We followed a non-random approach with some predetermined selection criteria (Smith, 1983). First, respondents should play key leadership roles (middle or senior management) in their hospitals, which should allow them to visualize and understand the hospital they represent and its specificities. Second, due to the high level of complexity intrinsic to healthcare organizations, we aimed for multiple respondents with diversified backgrounds and from different departments (i.e. clinician and non-clinician) within each hospital. Such requirement should provide a more holistic perception of the entire hospital and its H4.0 implementation experience, since evidence on applications of new information and communication technologies (ICTs) may vary from health treatments to administrative processes (Oueida et al., 2018). The use of multiple respondents per hospital also improves our study's internal validity and reliability (Brewer and Crano, 2000; Tabachnik and Fidell, 2007) and mitigates issues related to single-respondent bias (Hair et al., 2104). Despite the fact that no specific sampling criterion related to hospitals was established, we collected data from hospitals with different contextual characteristics. It is worth mentioning that all surveyed hospitals systematically tracked their performance results on a monthly basis, enabling a clearer perception of their respective respondents when answering the survey.

Data were collected during May and June 2018. Access to hospitals was relatively easy since the authors had already developed a network of hospitals from previous collaborative activities and studies. Each researcher used their contacts to send the questionnaire electronically or physically, depending on the hospital's preference, which significantly increased the response rate. In total, 267 respondents were initially contacted. The final sample combined 181 responses from 18 hospitals in six countries (see Table 2), which is an exceptionally high response rate (i.e. 67.8%) when compared to similar survey-based studies (Hair et al., 2014). Most respondents and hospitals were located in emerging economies (87.8% and 88.9%, respectively). Participants were predominantly from clinician departments (57.5%), performed Supervisor or Coordinator roles (69.6%) and had more than two years of experience in their roles (81.2%). Additionally, most respondents worked in private (59.7%) and teaching hospitals (61.3%), whose facilities were more than 20 years old (51.9%). In terms of size, 75.7% and 77.9% of respondents were from hospitals with less than 2,000 employees and more than 150 beds, respectively.

Table 2 – Sample characteristics (*n* = 181)

3.2. Development of data collection instrument and measures

The applied questionnaire had four parts (see Appendix). Initially, it collected information on respondents' characteristics, their departments and hospitals to determine the sample's demographic profile. Next, we asked respondents to score the adoption level of nine ICTs listed in Table 1 in their hospitals. Since the concept of H4.0 may not be understood by all respondents, those technologies were used as proxy for H4.0 implementation (a similar approach was adopted in other studies on the topic; e.g. Tortorella and Fettermann, 2018, and Rossini et al., 2019). To score the adoption level we used a five-point Likert scale, ranging from 1 (not used) to 5 (fully adopted). In the third part of the questionnaire, respondents were asked to score their hospitals' performance improvement in the past three years. According to Tortorella et al. (2019), variations in performance are usually easier to be observed and using such information as proxy for an organization's performance increases the validity of responses, especially when the sample is comprised mainly of middle managers. Five indicators were used to measure the performance improvement level (cost, productivity, quality, patient satisfaction, and patient safety). The impact of H4.0 on cost and productivity was emphasized by Ali et al. (2018) and Bradley et al. (2018). Wang et al. (2018a) suggested that the introduction of H4.0 technologies, such as Big Data and Cloud Computing, could enhance healthcare quality and patient satisfaction, while Cestari et al. (2017) highlighted the potential impact of new digital technologies on patient safety improvement. The five indicators were assessed using a five-point Likert scale, ranging from 1 (worsened significantly) to 5 (improved significantly). The last part of the questionnaire aimed at examining the criticality level of barriers against H4.0 implementation as perceived by respondents. For that, eight barriers gathered from the literature (see Table 1) were used as measures and evaluated in a five-point Likert scale, ranging from 1 (not critical) to 5 (highly critical).

Seven experts (four academicians and three practitioners) pre-tested the questionnaire to check its face and content validity, as recommended by Kothari (2004). Experts suggested minor corrections in taxonomy and the inclusion of a glossary with examples, which was sent along with the questionnaire. The glossary was particularly useful given the diversity in respondents' backgrounds (from Information Technology and Business Administration to Nursing and Medicine).

Our dataset was comprised of information obtained using psychometric scales applied to multiple respondents, and common method variance could potentially be an issue (Huber and Power, 1985). We conducted a few procedures to mitigate that. First, in terms of questionnaire design, dependent variables were presented far from independent variables (Podsakoff and Organ, 1986), and anonymity and confidentiality of the study were announced upfront to respondents, who were also informed that there were no right answers (Podsakoff et al., 2003). Regarding statistical verifications, we performed Harman's single-factor test (Malhotra et al., 2006) utilizing all study variables. Results pointed to a first factor explaining 26.3% of the total variance, which indicated that no single factor accounted for most of the variance in responses and that common method bias was not relevant.

3.3. Verification of constructs' validity and reliability

We performed three Exploratory Factor Analysis (EFA) using Principal Component (PC) extraction to validate constructs using questionnaire responses. According to Fabrigar et al. (1999), EFA is commonly used by researchers when developing a scale and serves to identify a set of latent constructs underlying a set of measured variables. It should be used when the researcher has no *a priori* hypothesis about factors or patterns of measured variables (Finch and West, 1997), which was our case. The same course of action was used in previous studies that aimed to identify and validate bundles of practices, such as Shah and Ward (2003), Tortorella et al. (2017), Moyano-Fuentes et al. (2019).

The first EFA was run on operational performance improvement indicators. Using a varimax rotation of axes we were able to obtain high loadings for the five performance indicators in the first PC, with an eigenvalue of 3.47 and accounting for 69.30% of the total variance in responses (see Table 3). Construct reliability was tested through the Cronbach's alpha; the result was α = 0.885, indicating high reliability in responses [according to Meyers et al. (2006)'s alpha threshold of 0.6 or higher].

Table 3 – EFA to validate the *operational performance improvement* construct

A second EFA was run using responses on the adoption level of the nine technologies presented in the questionnaire. The goal was to identify bundles of H4.0 technologies. Using a varimax rotation, we retained two PCs with eigenvalues larger than 1 (3.53 and 1.25, respectively); results are shown in Table 4. Analyzing the variable loadings in the components we were able to identify two bundles of technologies, which were named according to their predominant roles. Results were replicated using an oblique rotation as a check for orthogonality and the extracted components were similar. The unidimensionality of each component was verified and confirmed applying Principal Component Analysis at a component level. Reliability was assessed calculating Cronbach's alpha, with results displayed in Table 4. Responses for each bundle were obtained calculating a weighted average of original responses using factor loadings as weights.

The first bundle was comprised of digital technologies used for capturing (sensing) and communicating information about a patient, equipment, material or process; they are *Biomedical/Digital Sensors*, *IoT*, *Big Data*, *Cloud Computing* and *Remote Control/Monitoring*. Due to their similar purpose and following Aceto et al.'s (2018) suggestion, we named this bundle 'Sensing-Communication'. The second bundle was comprised of technologies that may change or process data producing actual information, moving or controlling a system, mechanism or software based on such information (Tortorella et al., 2020b); they are *3D Printing*, *Collaborative Robots*, *Machine/Deep Learning* and *Augmented Reality/Simulation*. The second bundle was named 'Processing-Actuation'.

Table 4 – EFA to validate bundles of H4.0 technologies–rotated component matrix

The third EFA was run using responses on the criticality level of eight barriers against H4.0 implementation. We run an EFA with varimax rotation to extract the two components in Table 5, with eigenvalues equal to or greater than 1. Two bundles were identified and empirically validated, with barrier variables loading on single factors. As H4.0 implies in fundamental changes in the way healthcare organizations operate, we followed indications from the STS theory (Hua, 2007; Sovacool and Hess, 2017) and named barrier bundles according to their nature; i.e. social or technical. Social barriers concern the emotional or intangible aspects that may impair H4.0 implementation, such as *misalignment with hospital´s strategy*, *poor knowledge about technologies*, *absence of a qualified team* and *difficulties in finding good partners*. Technical barriers refer to tangible or logical components that are considered critical in H4.0 implementation, such as *information security risks*, *implementing costs*, *regulatory changes* and *incorporated IT infrastructure*.

Table 5 – EFA to validate bundles of H4.0 implementation barriers–rotated component matrix

In addition to the EFA, we ran a Confirmatory Factor Analysis (CFA) including all bundles of H4.0 technologies and barriers (see Table 6) to confirm their convergent validity and unidimensionality (Tabachnik and Fidell, 2007). Because of the sample size constraints, we estimated two separate CFA models, as suggested by Bentler and Chou (1987): one for the complete model including all bundles, and another for each single bundle. CFA models were assessed to verify their goodness-of-fit based on Chi-squared test result (χ^2/df), Comparative Fit

Index (CFI) and Standardised Root Mean Square Residual (SRMR). CFI values greater than 0.90 combined with SRMR values lower than 0.08 were used as thresholds (Hu and Bentler, 1999). All items loaded satisfactorily on their constructs (factor loadings above 0.45) and all displayed acceptable Cronbach alpha levels. Discriminant validity was assessed through average variance extracted (AVE). Each bundle's value resulted greater than the squared correlation coefficients (Fornell and Larcker, 1981; Bagozzi and Yi, 1988). CFA models were run using the lavaan routine in R, and satisfactorily met the required thresholds. Composite reliability (CR) was also calculated for each bundle. CR values were larger than 0.7, confirming the convergent validity of constructs (Hair et al., 2014). Therefore, values for each validated construct were calculated based on their corresponding factor loadings and given in a continuous scale. Pairwise correlations for all constructs were determined, as shown in Table 7. Significant correlation coefficients (p-value < 0.05) were found positive or negative, indicating the nature of variables' interaction.

Table 6 – Bundles of H4.0 technologies and barriers, measures and CFA factor loadings

Table 7 – Pairwise correlation coefficients

3.4. Data analysis

In this step, we first grouped observations according to the adoption level of *Sensing-Communication* and *Processing-Actuation* technologies. For that, the median response value of each bundle was used as threshold to differentiate low and high adopters. In the case of *Sensing-*

Communication, 89 observations were positioned below the threshold, being grouped as 'Low Adopters'; remaining 92 observations with responses above the threshold were denoted 'High Adopters'. For *Processing-Actuation*, 88 respondents had adoption levels below the bundle's threshold and were categorized as 'Low Adopters'; remaining 93 observations were assigned to the 'High Adopters' group.

A similar procedure was adopted to classify observations according H4.0 barriers. The median response values of *Technical* and *Social* barrier bundles were used as thresholds for categorizing respondents as 'Lowly Constrained' or 'Highly Constrained'. Regarding *Technical* barriers, 80 observations were classified as Lowly Constrained and 101 as Highly Constrained; regarding *Social* barriers, 80 respondents were classified as Lowly Constrained and 101 as Highly Constrained.

The effect of H4.0 technology adoption (i.e. *Sensing-Communication* and *Processing-Actuation*) was tested on hospitals' performance improvement (dependent variable) through a one-way ANOVA (analysis of variance). The objective was to test *H1*. To verify the interacting effect between H4.0 technologies and barriers on hospitals' performance improvement (and test *H2*), a Two-way ANOVA was applied testing pairs of H4.0 technologies and barriers. Residuals from both models (One- and Two-Way ANOVAs) were tested for normality using the Kolmogorov-Smirnov test. Results indicated errors normally and independently distributed.

Whenever both main and interaction effects were significant, we disregarded the main effect as suggested by Montgomery (2013). It is noteworthy that, although a minimum sample size is not required to perform ANOVAs (Meyers et al., 2006), we did not test the full factorial model (and higher-order interactions) due to the small sample size.

4. Results

Table 8 displays the ANOVA results. As envisioned by Sultan (2014), Yang et al. (2015) and Wang et al. (2018a), H4.0 technologies seem to have a significant impact on hospitals' performance improvement. In fact, our results show that both bundles of H4.0 technologies are positively associated with hospitals' performance. The average performance improvement levels of high adopters of *Sensing-Communication* and *Processing-Actuation* (0.382 and 0.321, respectively) were higher than the ones observed for low adopters (-0.366 and -0.309, respectively), indicating that hospitals may benefit from their adoption. These results are somewhat expected in light of popular knowledge, which suggests that ICTs integration allows faster and more efficient processes in healthcare organizations. Further, our outcomes corroborate to findings from Garai et al. (2017) and Wang et al. (2018b), who have conducted experimental studies in specific areas/treatments within a hospital. Thus, when analyzed their main effects, H4.0 technologies do seem to positively impact hospitals' performance improvement in a general sense.

Table 8 – ANOVA results

When considering the interaction effects between H4.0 technologies and barriers, two associations appear significant: (*i*) *Sensing-Communication* technologies and *Technical* barriers, and (*ii*) *Processing-Actuation* technologies and *Social* barriers. Table 9 shows the estimated marginal means of those interactions, assuming a 90% confidence interval. Analyzing the levels of the interaction between *Sensing-Communication* technologies and *Technical* barriers, we conclude that when hospitals' leaders do not perceive *Technical* barriers as a major constraint for H4.0 implementation (Lowly Constrained), the difference in performance improvement between hospitals that are low adopters of *Sensing-Communication* technologies and high adopters is significant, with high adopters performing much better. That difference in performance is smaller in hospitals that are highly constrained by *Technical* barriers, as graphically displayed in Figure 2. These findings indicate that the positive impact of *Sensing-Communication* technologies on hospitals' performance is mitigated by a higher level of *Technical* barriers. That is aligned with findings in Baker et al. (2017) and Abdellatif et al. (2019), who emphasized that certain *Technical* barriers, such as *information security risks* and *IT infrastructure*, could compromise the expected benefits derived from H4.0 implementation. As healthcare regulations and accrediting organizations vary, different requirements are imposed on hospitals that invest significant efforts to achieve compliance (Vogenberg and Smart, 2018). Such efforts are usually capital- and time-consuming and tend to challenge the establishment of efficient information and communication processes within the hospital (Menon and Lee, 2000; Sittig and Singh, 2015). Our results support these indications and confirm that *Technical* barriers are a relevant challenge to be overcome throughout the H4.0 implementation, especially when adopting technologies focused on the acquisition and dissemination of health-related information. In other words, hospitals that wish to improve their processes, services and treatments through the adoption of *Sensing-Communication* technologies may need to firstly mitigate the inherent *Technical* barriers, so that they can perceive greater benefits from such digital transformation.

Table 9 – Estimated marginal means for hospitals' performance improvement level based on interactions between H4.0 technologies and barriers

The analysis of the interaction between *Processing-Actuation* technologies and *Social* barriers shows different results. Contrary to common belief, performance improvement gap between Low and High Adopters was more prominent when leaders believe their hospitals are highly constrained by *Social* barriers. The gap in performance improvement between Low and High Adopters in hospitals that are lowly constrained by *Social* barriers is not significant, as displayed in Figure 3. *Processing-Actuation* technologies process the acquired data producing actual information in a detectable way, resulting in movements of mechanisms (Zhang et al., 2017), decision-making support (Munzer et al., 2019) or system/software controls (Pardede, 2018). If not properly adopted, these technologies may be viewed as inhibitors of job autonomy and significance. The concern that the increasing automation and digitalization promoted by the fourth industrial revolution negatively impact social aspects in workplaces has motivated several studies (e.g. Dombrowski and Wagner, 2014; Dworschak and Zaiser, 2014; Benešová and Tupa, 2017; Arntz et al., 2016). In general, those studies point that higher levels of automation may change labor skills and requirements in organizations. *Social* barriers refer to customers, suppliers, employees and the knowledge, skills, attitudes, values, rules and needs they bring to the work environment (Cecconi, 2016; Sovacool and Hess, 2017). It is somewhat reasonable that in hospitals where these barriers are less critical, their interaction with *Processing-Actuation* technologies does not display a significant effect on performance improvement. In opposition, when *Social* barriers are critical, High Adopters of *Processing-Actuation* technologies have a significant performance improvement. In other words, in hospitals where labor skills, knowledge and attitudes are a relevant issue to be addressed, the implementation of *Processing-Actuation* technologies appears to help mitigating the negative effect of those barriers. The fact that *Processing-Actuation* technologies imply significant shifts on the way people work might counterbalance the negative effect of *Social* barriers, leading to more noticeable differences in performance variations of the hospitals. When *Social* barriers are not an issue, the performance variation entailed by the adoption of *Processing-Actuation* technologies is not as prominent.

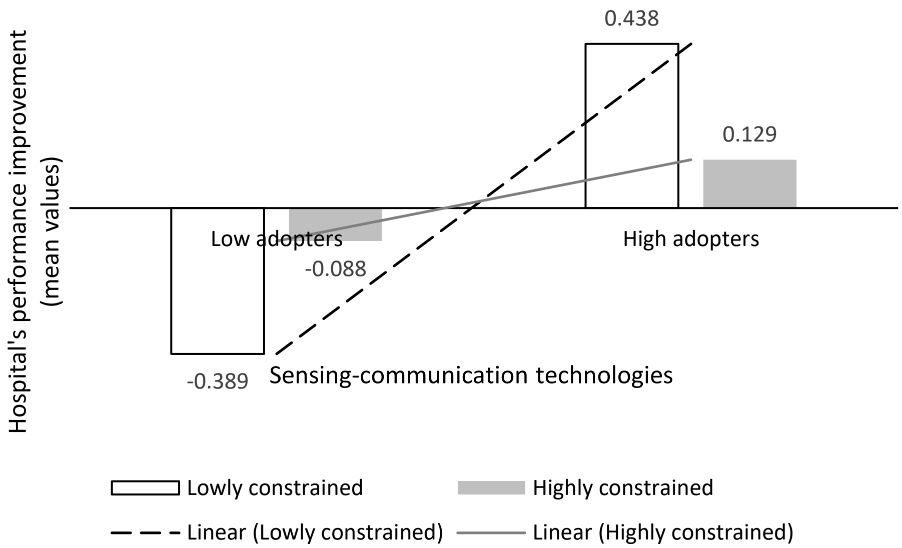

Figure 2 – Interaction between *Sensing-Communication* technologies and *Technical* barriers

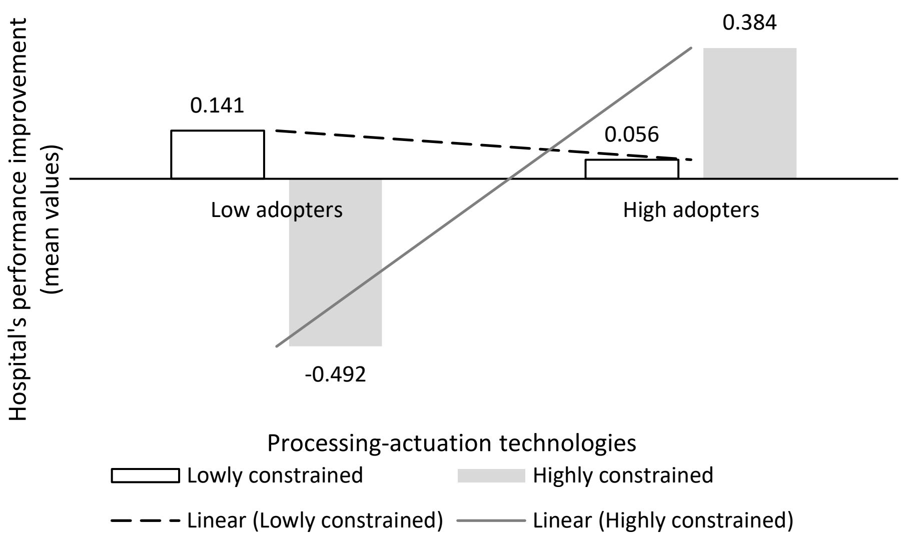

Figure 3 – Interaction between *Processing-Actuation* technologies and *Social* barriers

5. Discussions and Conclusions

In this paper, we have studied the main effects of H4.0 technologies and barriers and their interaction effect on hospitals' performance improvement. This research suggests two major findings. First, H4.0 technologies could be organized into two different bundles. Similarly, the most common barriers for H4.0 implementation could also be combined into two bundles. Second, these bundles of H4.0 technologies do present a positive and significant association with hospitals' performance. As their interaction with H4.0 barriers was also found relevant for performance improvement, it is important to concurrently consider H4.0 technologies and barriers to understand their impact on hospitals. We provide a deeper discussion on both findings in the following sections.

5.1. H4.0 bundles

Prior studies (e.g. Sharma et al., 2016; Aceto et al., 2018) have suggested different frameworks for supporting digital transformation in healthcare organizations. However, the combination of H4.0 technologies into bundles and their empirical validation has not yet been reported in the literature. Therefore, a contribution of this research is that we identify two specific technology bundles and we empirically validate them through PCA, finding results that are consistent with the literature.

The *Sensing-Communication* bundle combines five H4.0 technologies. One of them, *Biomedical/Digital Sensors*, is mainly focused on providing means for data acquisition from patients and equipment. Once data and information are acquired, they should be transmitted. *IoT* enables the interconnection between people, materials and equipment, favoring the agile exchange of information in the hospital. Due to such enhanced interconnection, large amounts of diversified data are constantly generated, establishing the need for properly storing and organizing/synthesizing data into useful information. *Cloud Computing* and *Big Data* provides the means for that, contributing for a successful communication process within hospitals. Finally, information availability allows real-time and remote monitoring of processes, patients, materials and equipment, which is facilitated by the *Remote Control or Monitoring* technology.

The *Processing-Actuation* bundle combines technologies that allow transforming the information previously acquired and communicated into decisions or actions needed in healthcare processes. Four H4.0 technologies integrate that bundle. The first one is *Machine/Deep Learning*, whose objective is to enable computers to learn automatically without human intervention or assistance, and adjust actions accordingly. Such actions may vary from physical interaction between robots and physicians (*Collaborative Robots*) to jointly perform a surgery, to the manufacturing of a three-dimensional medical instrument based on a computer-aided design project, usually by successively adding material layer by layer (*3D Printing*). The ability to process information is also facilitated through *Augmented Reality*/*Simulation*, as it provides an interactive experience of a real-world environment where objects are enhanced by computer-generated perceptual information, whose application varies from medical images (e.g. tomography and magnetic resonance imaging) to emergency medicine.

Finally, the definition and validation of two bundles of barriers (*Technical* and *Social*) help to establish the underlying challenges that surround H4.0 implementation. The theoretical basis for these bundles emerges from sociotechnical systems theory, which assumes the interrelatedness between social (intangible and/or emotional) and technical (tangible) aspects for a successful organizational development (Walker et al., 2008). Sociotechnical systems theory indicates that both social and technical systems should be designed and improved together, and there may be multiple ways for achieving their joint optimization (Cecconi, 2016). Thus, the identification and consideration of these bundles are useful for researchers conducting studies on how to overcome technical and social barriers to H4.0 implementation, and to test hypotheses about their relationships with other characteristics that might affect performance. We argue that their empirical validation allows a more holistic assessment of the existing conditions for H4.0 implementation in hospitals. Our findings are particularly useful for future studies aimed at mapping organizations to detect areas of resistance to H4.0 adoption (Heifetz et al., 2009).

5.2. H4.0 bundles and hospitals' performance improvement

Results indicate that the adoption of H4.0 technologies from both bundles identified in this research improves hospital performance, supporting *H1*. However, when considering the interaction between bundles of H4.0 technologies and *Technical* and *Social* barriers, unexpected effects on performance are observed. In general, our study provided evidence that the interaction between H4.0 technologies and barriers significantly affects hospitals' performance improvement, supporting *H2*; however, the magnitude of interaction effects may vary according to the technologies and barriers under consideration.

Two types of interactions stood out as significant to explain hospitals' performance improvement. The first one relates *Technical* barriers and *Sensing-Communication* technologies. We found a large performance improvement gap between low and high adopters of sensing-communication technologies that are lowly constrained by technical barriers. In fact, low technology adopters present a negative performance improvement of -0.39, while high technology adopters present a positive performance improvement of +0.44. The performance improvement gap between low and high adopters of sensing-communication technologies that are highly constrained by technical barriers is much smaller, although still significant.

The second interaction relates *Social* barriers and *Processing-Actuation* technologies. We found a large performance improvement gap between low and high adopters of processing-actuation technologies that are highly constrained by social barriers, with low adopters displaying a negative improvement of -0.49 and high adopters a positive improvement of +0.38. The performance gap between low and high adopters in hospitals lowly constrained by social barriers is much smaller and not significant. This counterintuitive outcome suggests that benefits from this bundle of technologies are more visible when hospitals struggle with knowledge, skills, attitudes, values and needs inherent to H4.0 implementation. Such unexpected result is somewhat aligned with a key principle of sociotechnical systems theory, which states that the individual and unilateral reinforcement of either social or technical aspects may lead to undersigned relationships that can harm organizational performance (Cooper and Foster, 1971). That seems to be particularly prominent when considering the interaction between *Social* barriers and *Processing-Actuation* technologies.

5.3. Managerial implications

Our research also provides some practical contributions to hospitals that are implementing H4.0. First, due to the empirical validation of bundles of technologies, those hospitals may benefit from the concurrent adoption of these sets of interrelated technologies. As H4.0 demands a significant capital expenditure to set the required infrastructure and skills in place, determining which technologies could synergistically interact could save managerial efforts and catalyze implementation benefits. The identification of technology bundles establishes a basic implementation framework that guides hospitals towards their digital transformation in a more assertive way.

Additionally, the verification of a positive relationship between bundles of technologies and hospitals' performance provides evidence on the potential benefits that H4.0 may entail in healthcare organizations. This result is especially relevant due to the characteristics of the sample investigated in this study, comprised of hospitals located in emerging (Brazil, Mexico, Argentina and India) and developed (USA and Italy) economies. Our research indicated that H4.0 implementation may positively impact hospitals regardless of the socioeconomic context in which they are inserted. Previous studies (Dworschak and Zaiser, 2014; Lasi et al., 2014; Rossini et al., 2019) inferred that implementing high-tech approaches could be more attractive in contexts where qualified labor and capital capacity are more abundant. Our study does not validate such assumption, encouraging hospitals and leaders to adopt H4.0 despite socioeconomic issues.

Finally, the understanding on how the interaction between H4.0 technologies and barriers affects performance improvement has direct implications for hospitals' leaders. As leaders become aware of their internal challenges (either social or technical) for H4.0 implementation, they may be able to anticipate which technologies are more likely to promote better performance results. Further, since hospitals are composed by several clinician and non-clinician departments, the criticality of *Social* and *Technical* barriers may vary significantly among them, leading to conditions more or less favorable to H4.0 implementation. The awareness of such specificities allows leaders to customize H4.0 implementation, avoiding a potentially ineffective "one-size-fits-all" approach.

5.4. Limitations and future research

The main limitation of our study concerns the H4.0 implementation itself. The Fourth Industrial Revolution has been acknowledged in 2011 and literature evidence on H4.0 initiatives is prolific. However, studies on H4.0 implementation mostly focuses on early stages, reporting isolated applications in specific departments or processes. This suggests that the extension of H4.0 implementation and its maturity level may vary significantly across hospitals, influencing respondents' perceptions on the subject. Although we adopted countermeasures to curb perception biases (e.g. establishing sample selection criteria and surveying multiple respondents per hospital), we understand that larger sample sizes would help overcome such issues and allow more robust inferences. Furthermore, our analyses did not consider specific contextual variables. Although our approach was consciously carried out since the study from Tortorella et al. (2020a) had already addressed the effects of contingencies on H4.0 implementation, we acknowledge that examining the effects of contextual variables in this association between H4.0 technologies and barriers towards enhanced performance levels would feature a novel contribution. Additionally, as we performed a cross-sectional study, the maturity issue might be more difficult to observe. The development of longitudinal studies would enable the comprehension on how social and technical aspects evolve as H4.0 is being implemented in hospitals. Such extension would require a more elaborate data collection and analysis, being a topic for future research.

Finally, we examined the effect of H4.0 implementation based on a specific set of digital technologies. From this set, we identified bundles and their association with performance improvement. As the body of knowledge on H4.0 advances, other technologies might be included in the H4.0 portfolio, resulting in complementary bundles whose relationship with hospitals' performance may differ, opening another opportunity for future research. Performance indicators used in our instrument could also be expanded to include ‘staff safety’, which is a relevant issue in healthcare organizations, especially in terms of contamination hazards to which hospital personnel may be exposed. Additionally, future studies that utilize computational simulation tools would be able to examine critical conditions of hospitals performance and how H4.0 implementation could support them in such extreme contexts.

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

Table 2 – Sample characteristics (*n* = 181)

Respondents per country			Hospital's age			Respondent's role		
Brazil	67	37.0%	< 20 years	87	48.1%	Supervisor or Coordinator	126	69.6%
India	36	19.9%	> 20 years	94	51.9%	Manager or Director	55	30.4%
Mexico	34	18.8%	Teaching Hospital			Respondent's experience in the role		
Argentina	22	12.1%	No	70	38.7%	< 2 years	34	18.8%
USA	16	8.9%	Yes	111	61.3%	> 2 years	147	81.2%
Italy	6	3.3%	Hospital's ownership			Department type		
Hospitals per country			Public	73	40.3%	Non-clinician	77	42.5%
Brazil	9	50.0%	Private	108	59.7%	Clinician	104	57.5%
India	3	16.6%	Number of beds			Clinician department (*n* = 104)		
Mexico	3	16.6%	< 150	40	22.1%	Nursing	59	56.7%
Argentina	1	5.6%	> 150	141	77.9%	Medical	45	43.3%
USA	1	5.6%	Number of employees			Respondents per socioeconomic context		
Italy	1	5.6%	< 2,000	137	75.7%	Emerging economies (Brazil, India, Mexico and Argentina)	159	87.8%
			> 2,000	44	24.3%	Developed economies (USA and Italy)	22	12.2%

Table 3 – PCA to validate the *operational performance improvement* construct

Performance indicators	Mean	Std. dev.	Communalities	Factor
Cost	3.10	1.11	0.518	**0.720**
Productivity	3.36	1.05	0.657	**0.811**
Quality	3.57	1.03	0.810	**0.900**
Patient satisfaction	3.68	0.96	0.674	**0.821**
Patient safety	3.75	0.98	0.805	**0.897**
Eigenvalue				3.47
Percentage of variance explained				69.30
Cronbach's α (*n* = 181)				0.885
Kaiser-Meyer-Olkin Measure of Sampling Adequacy				0.802
Bartlett's Test of Sphericity (χ2 / dF)				590.18 / 10 (*p*-value < 0.01)

Table 4 – PCA to validate bundles of H4.0 technologies–rotated component matrix

H4.0 technologies	Mean	Std. dev.	Communalities	Component 1	Component 2	Role
Biomedical/Digital sensors	2.95	1.38	0.470	**0.685**	-0.008	Sensing-Communication
IoT	2.63	1.53	0.537	**0.727**	0.088	
Big data	2.12	1.37	0.580	**0.726**	0.230	
Cloud computing	2.56	1.44	0.421	**0.637**	0.120	
Remote control or monitoring	2.17	1.30	0.506	**0.600**	0.382	
3D printing	1.52	0.99	0.389	-0.027	**0.623**	Processing-Actuation
Collaborative robots	1.39	0.97	0.694	0.231	**0.800**	
Machine/Deep learning	1.66	1.15	0.604	0.517	**0.580**	
Augmented reality/simulation	1.73	1.11	0.582	0.158	**0.746**	
Eigenvalues				3.53	1.25	
Initial percentage of variance explained				39.26	13.86	
Rotation sum of squared loadings (total)				2.64	2.14	
Percent of variance explained				29.32	23.80	
Cronbach's α (*n* = 181)				0.739	0.706	
Kaiser-Meyer-Olkin Measure of Sampling Adequacy				0.828		
Bartlett's Test of Sphericity (χ2 / dF)				419.30 / 36 (*p*-value < 0.01)		

Table 5 – PCA to validate bundles of H4.0 implementation barriers–rotated component matrix

H4.0 implementation barriers	Mean	Std. dev.	Communalities	Component 1	Component 2	Orientation
Misalignment with hospital´s strategy	2.93	1.17	0.547	**0.554**	0.490	Social
Poor knowledge about technologies	2.99	1.24	0.752	**0.849**	0.178	
Absence of a qualified team	2.81	1.26	0.745	**0.826**	0.250	
Difficulties in finding good partners	2.98	1.16	0.654	**0.783**	0.202	
Information security risks	2.99	1.23	0.604	0.371	**0.683**	Technical
Implementing costs	2.70	1.44	0.367	0.391	**0.463**	
Regulatory changes	2.97	1.22	0.652	0.055	**0.806**	
Incorporated IT infrastructure	2.94	1.20	0.596	0.237	**0.734**	
Eigenvalues				3.91	1.00	
Initial percentage of variance explained				48.93	12.53	
Rotation sum of squared loadings (total)				2.67	2.24	
Percent of variance explained				33.41	28.05	
Cronbach's α (*n* = 181)				0.831	0.715	
Kaiser-Meyer-Olkin Measure of Sampling Adequacy				0.849		
Bartlett's Test of Sphericity (χ2 / dF)				521.75 / 28 (*p*-value < 0.01)		

Table 6 – Bundles of H4.0 technologies and barriers, measures and CFA factor loadings

Bundles	Measures	Coef.	AVE	χ^2/df	CFI	SRMR	CR
Sensing-Communication	Biomedical/Digital sensors	0.701	0.584	10.861/3	0.912	0.059	0.796
	IoT	0.698					
	Big data	0.754					
	Cloud computing	0.612					
	Remote control or monitoring	0.605					
Processing-Actuation	3D printing	0.638	0.593	9.002/2	0.924	0.069	0.700
	Collaborative robots	0.785					
	Machine/Deep learning	0.597					
	Augmented reality/simulation	0.719					
Social barriers	Misalignment with hospital´s strategy	0.601	0.529	8.078/2	0.909	0.075	0.830
	Poor knowledge about technologies	0.901					
	Absence of a qualified team	0.817					
	Difficulties in finding good partners	0.794					
Technical barriers	Information security risks	0.655	0.552	12.891/2	0.911	0.065	0.720
	Implementing costs	0.481					
	Regulatory changes	0.821					

Incorporated IT infrastructure	0.705

Table 7 – Pairwise correlation coefficients

Variables	1	2	3	4	5
1-Technical barriers	-	0.594**	-0.143	-0.141	-0.174*
2-Social barriers		-	-0.126	-0.088	-0.128
3-Performance improvement			-	0.203**	0.404**
4-Processing-Actuation technologies				-	0.493**
5-Sensing-Communication technologies					-

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

Table 8 – ANOVA results

Independent variables	Hospitals' performance improvement *F*-values
Sensing-Communication	13.20***
Processing-Actuation	7.54***
Sensing-Communication x Technical barriers	2.60*
Sensing-Communication x Social barriers	0.04
Processing-Actuation x Technical barriers	0.02
Processing-Actuation x Social barriers	6.21**

Note: * *p*-value < 0.10; ** *p*-value < 0.05; *** *p*-value < 0.01.

Table 9 – Estimated marginal means for hospitals' performance improvement level based on interactions between H4.0 technologies and barriers

H4.0 barriers		H4.0 technologies		Mean	90% Confidence interval	
					Lower bound	Upper bound
Technical barriers	Lowly constrained	Sensing-Communication	Low adopters	-0.389	-0.684	-0.094
			High adopters	0.438	0.181	0.694
	Highly constrained		Low adopters	-0.088	-0.344	0.168
			High adopters	0.129	-0.131	0.389
Social barriers	Lowly constrained	Processing-Actuation	Low adopters	0.141	-0.150	0.431
			High adopters	0.056	-0.185	0.297
	Highly constrained		Low adopters	-0.492	-0.767	-0.216
			High adopters	0.384	0.118	0.650

Appendix – Questionnaire

I- Please, provide below the information about you, your department and the hospital you work for.

1 – Your professional profile:

a) Role: ( ) Supervisor/Coordinator ( ) Manager/Director

b) Experience in your role: ( ) < 2 years ( ) 2 years

2 – Your department: ( ) Clinician ( ) Non-clinician

3 – Your hospital:

a) Hospital's age: ( ) > 20 years ( ) < 20 years

b) Teaching hospital: ( ) No ( ) Yes

c) Hospital's ownership: ( ) Public ( ) Private

d) Number of beds: ( ) < 150 beds ( ) > 150 beds

e) Number of employees: ( ) < 2,000 ( ) > 2,000

II- Please, indicate below the adoption level of the following digital technologies in your hospital.

Digital technologies	Not used				Fully adopted
	1	2	3	4	5
Biomedical/Digital sensors					
3D printing					
Collaborative robots					
IoT					
Big data					
Cloud computing					
Machine/Deep learning					
Augmented reality/simulation					
Remote control or monitoring					

III- Please, indicate below the improvement level of the following performance indicators in the past three years in your hospital.

Performance indicator	Worsened significantly				Improved significantly
	1	2	3	4	5
Cost					
Productivity					
Quality					
Patient satisfaction					
Patient safety					

IV- Please, indicate below the criticality level of the following barriers for digital technologies implementation in your hospital.

Performance indicator	Not critical				Highly critical
	1	2	3	4	5
Regulatory changes					
Incorporated IT infrastructure					
Misalignment with hospital´s strategy					
Information security risks					
Implementing costs					
Poor knowledge about the technologies					
Absence of a qualified team					
Difficulties for finding good partners					