How Can Technological Resources Improve the Quality of Healthcare Service? The Enabling Role of Big Data Analytics Capabilities

Luigi Jesus Basile, Nunzia Carbonara, Umberto Panniello, and Roberta Pellegrino

Abstract—**The increasing adoption of digital technologies is revolutionizing healthcare professionals' activities. These technologies generate large amounts of data that can be used by big data analytics (BDA) to extract knowledge that, if properly utilized, may support the decision-making process and ultimately improve the quality of healthcare services. Although hospitals have been investing in BDA technological resources, it seems that the quality of service has not always been improved. In recent years the academic literature highlighted the relevance of BDA capabilities in improving organizations' performance, but their role in healthcare organizations seems overlooked. The purpose of this study is to empirically investigate the relationship between BDA technological resources and capabilities and the quality of healthcare services. It also aims to determine whether the presence of BDA capabilities in healthcare organizations can be the underlying mechanism that explains the effect of BDA technological resources on the quality of healthcare services. In total, 173 responses from Italian healthcare professionals were collected and investigated via the lens of resource-based view theory using the partial least square structural equation modeling methodology. The results show the pivotal role of BDA capabilities in deploying BDA technological resources to improve the quality of healthcare services and thus the need for further investment in BDA capabilities.**

Index Terms—**Big data, digital health, digital transformation, health, healthcare, hospital, quality of services, resource-based view (RBV).**

I. Introduction

The spread of new technologies pushed the digitalization of many firms, thus generating deep changes and disruptions in recent years and driving growth in many industries [1], [2]. The healthcare industry is one of the main beneficiaries of this shift among others [3], [4], [5], [6]. Technologies paradigms such as cloud computing, big data, and the internet of things are leading this industry toward the so-called "Healthcare 4.0" [7], [8]. Among the most widely employed technologies in healthcare, there are wearables and portable technologies, telemedicine, and electronic health records [9]. These technologies support physicians in following the paradigm of "the right care at the right time and right place" [10]. Wearables and portables enable the collection of patient health data every time and everywhere [11], telemedicine is a set of technologies that assist physicians and patients in delivering and receiving healthcare services remotely [12], while an electronic health record is "a repository of patient data in digital form, stored and exchanged securely, and accessible by multiple authorized users" [13], that can be exploited for instance to support diagnosis, prognosis, or treatment choices [14], [15], [16]. These technologies are unique in their ability to generate and capture large amounts of data, e.g., patient administrative data [5], [17]. The availability of this data offers the opportunity to extract knowledge and, if properly utilized, to support decision-making [18], [19], [20]. Big data analytics (BDA) are used to leverage these massive amounts of data. BDA refers to the technologies, processes, and methodologies that analyze large amounts of data to assist an organization in improving the visibility and velocity of relevant information leading to more informed critical decisions [17], [21], [22], [23]. This is considered relevant given that healthcare decisions are characterized by high risk and uncertainty [24], [25], due to the lack of information [26], which can be mitigated by extracting the information from the available data in healthcare organizations. One of the most promising uses of BDA in healthcare organizations is the exploitation of data to increase the visibility and transparency of processes and to ease collaboration among professionals [27]. Thus, in healthcare, the use of BDA seems really promising to deal with risk and uncertainty in the decision-making process with the aim of increasing the quality of healthcare services, which can be assessed in three dimensions, namely professional and organizational resources (structure), tasks performed for the patient (process), and the desired outcome of the care provided by healthcare professionals (outcome) [28]. Past literature mainly focused on the effective acquisition and deployment of BDA technological resources (BDATR), such as infrastructure, intelligence, and analytics tools to support the decision-making processes [29]. However, the mere presence of technological resources may not guarantee their optimal use [17], [30] and consequently their impact on the quality of healthcare services. For example, the U.K. National Health Service lost more than £10 billion by failing to implement patient medical records that aimed to support healthcare professionals' decision-making through data analytics [31]. One of the reasons for this failure is considered to be the lack of capabilities of the analytical team of the project, rather than the lack of

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The authors are with the Department of Mechanics Mathematics and Management, Polytechnic University of Bari, 70126 Bari, Italy (e-mail: luigijesus.basile@poliba.it).

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technological resources [32]. In this context, in the last few years, several researchers have focused also on the managerial and organizational aspects that impact the effective employment of these technologies [33], [34], [35], [36]. Among these, the presence or development of digital capabilities is considered one of the factors that can lead to better organizational performance [37], [38], [39], [40], [41]. However, despite the growing interest in the use of BDA technological resources and capabilities to improve decision-making in healthcare, their effect on the quality of healthcare services domains seems to be overlooked by empirical studies in the academic literature. In this regard, existing literature mainly focused on the effect of BDA capabilities on others performance in healthcare organizations, such as the operational and environmental ones [20], [42], without considering the BDATR. This study aims to empirically investigate the relationship between BDA technological resources and capabilities with the quality of healthcare services domains (i.e., structure, process, and outcome), and if the presence of BDA capabilities (BDAC) in healthcare organizations can explain the effect that the BDATR have on the quality of healthcare services domains, namely the structure, the process, and the outcome. To this aim, we developed a research model grounded on the resource-based view (RBV) theory since it may provide a basis for identifying and assessing the significance of the relationship of the BDA technologies resources and capabilities with the quality of healthcare services. In light of this, the following research question is sought to be addressed.

Is the presence of BDAC an explaining mechanism of the effect of BDATR in improving the quality of healthcare services domains?

The rest of this article is organized as follows. In Section II, we presented the theoretical background and the hypotheses development. In Section III, we briefly presented the methodology adopted in this study. In Section IV, we presented results, and in Section V, we subsequently elaborated the discussion of the study, highlighting the practical and academic implications. Finally, Section VI, concludes this article.

II. Theoretical Background and Hypotheses Development

A. RBV Theory and BDA

The RBV is among the most relevant and discussed managerial theories [43], [44]. RBV theory is particularly useful in examining how an organization can leverage its unique resources and capabilities to achieve a sustainable competitive advantage [45]. In particular, RBV theory emphasizes the importance of internal resources and capabilities rather than external factors such as market conditions or industry trends [43]. Academic researchers and practitioners applied this theory through the use of a set of tools to assess the resources and capabilities an organization might possess and the potential of each of these to generate competitive advantages. In particular, early versions of the RBV referred to a VRIN framework, which suggests that a firm's competitive advantage is based on its ability to develop and exploit resources that are valuable (V), rare (R), inimitable (I), and nonsubstitutable (N) (VRIN) [45], [46]. However, the contemporary version subsumes the nonsubstitutability requirement of VRIN under the imperfectly imitable condition and adds organizational processes, as a means for exploiting the potential of VRI resources [38]. Then the VRIN model evolved to the VRIO framework, where the change of the last letter of the acronym refers to the so-called question of "organization," which is the ability of the firm to exploit the resource or capability. Accordingly, the VRIO framework assesses the value (V), rarity (R), inimitability (I), and organization of resources (O) to determine their competitive advantage [45]. This theory is one of the most used among organizational studies about the use of BDA resources and capabilities [47], [48]. The academic literature on BDA resources and capabilities has shown that they have the potential to establish a competitive advantage that leads to improved firm performance [41], [49], [50], [51]. Wade and Hulland [44], drawing on RBV theory, showed that BDAC can lead to a competitive advantage when the firm's organization exploits the potential of these resources because they are considered valuable, rare, and imperfectly imitable. Moreover, Gupta and George [52] identified the bundle of organizational resources to develop BDA capabilities and validated the positive relationship between capabilities and a firm's operational and market performance. In particular, BDA capabilities to be properly developed need technological, cultural, technical, and managerial skills as basic resources [41]. Also, the BDA capabilities can be drawn as a composition of three main capabilities, namely technology, management, and talent capabilities, and they are considered as the discriminator of the difference in BDA implementation success between organizations [49]. Moreover, the literature explored the relationship between BDA capabilities and the creation of business value pointing out the potential of BDA in supporting the development of new activities or in identifying areas of improvement in order to obtain a competitive advantage [29]. More recently scholars focused on the relevance of BDA capabilities in healthcare and their great potential in this industry to pursue value-based healthcare that leads to competitive advantage [53], e.g., the effective exploitation of data can lead to assist and improve diagnosis processes or deliver customized health services [48], [54]. Wang et al. [17] defined BDA capabilities as "the ability to acquire, store, process and analyze large amounts of health data in various forms, and deliver meaningful information to users that allow them to discover business values and insights in a timely fashion." Moreover, they explored the potential benefits it may bring to healthcare organizations such as the improvement of the accuracy of clinical decisions, reduce the time of patient travel, and identify new insights about health population trends [17]. In this context, Yu et al. [20] discussed and demonstrated how culture and mindset resources are effectively managed and bundled to create BDA capabilities in order to obtain optimal operational performance in healthcare organizations.

B. Theoretical Model and Research Hypotheses

BDA technologies are revolutionizing service delivery in healthcare organizations, e.g., by ensuring patient-centered services and operational efficiencies [3], [5]. Despite their promising relevance, the academic literature on healthcare services points out that the investment and acquisition of these technologies do not guarantee their effective use to gain strategic knowledge and insights to ultimately improve the quality of services [29]. In this regard, quality performance improvement could be achieved with the development of BDA capabilities [29], which can be outlined as the ability to collect, analyze, and visualize big data [55]. However, to date, there is limited empirical research in the healthcare organizations setting that investigates the role of BDA technological resources and capabilities in ensuring the quality of healthcare services from the perspective of healthcare professionals. Thus, in this context, this study proposes a research model grounded on RBV theory that investigates the effect of BDATR and BDAC in improving the quality of services' domains (i.e., quality of structure, process, and outcome) and whether the presence of BDAC could be an enabling factor that explains the effect of the BDATR on the quality of healthcare services' domains. In the following, the hypotheses will be developed.

C. Effects of BDATR and BDAC on the Quality of Healthcare Services' Domains

In the current years, the use of digital technologies in healthcare organizations is boosting the quality of healthcare services [5], [56]. Among the most promising technologies, there are BDA [8], [17]. Healthcare organizations produce large amounts of data by performing simple daily activities, which can be leveraged by BDA to ultimately improve the quality of healthcare services [17]. The quality of these services can be drawn from three main domains: structure, process, and outcome [28]. For instance, in the structure domain, it is possible to have information about the resources needed (e.g., medical equipment) by predicting the number of patients that require hospitalization [57]. While in the process domain, BDA can support physicians in the diagnosis and treatment decisions [58], [59] or in the outcome domain to understand what affects in-patient mortality [60]. Drawing on the RBV theory, healthcare organizations need both BDATR and BDAC to ensure the optimal performance of healthcare services.

Considering the technological resources, healthcare organizations are investing in digital technologies to collect, store, and exploit large amounts of data [5], [15]. For instance, among the most adopted technologies in healthcare, there are electronic health records, telemedicine, and wearable devices [9]. There is a growing awareness among healthcare organizations that adopting these resources may provide better care and services to patients [5], [11], [12]. Therefore, we proposed the following hypotheses.

- BDA technological resources have a positive impact on the domains of healthcare service quality, in terms of structure (H1a), process (H1b), and outcome (H1c).

Considering the capabilities, BDAC can also be defined as the organization's unique and inimitable abilities to efficiently use big data to gain strategic knowledge and insights [37]. Particularly, in the academic literature, the role of BDAC is proposed as a leading factor of success in the implementation of big data projects rather than the result of investments in resources

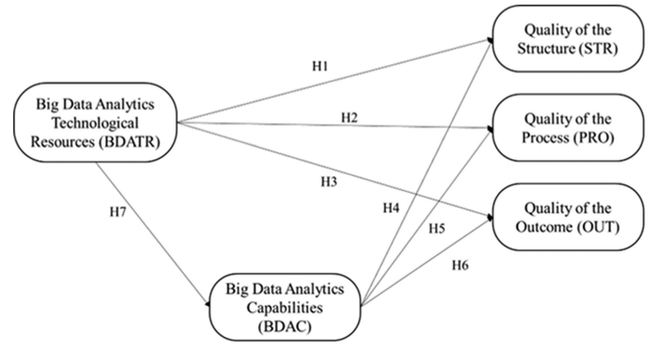

Fig. 1. Research model.

[52], [61], [62]. Thus, this capability could be considered as an enabler of the effective use of data to inform the decision-making process in healthcare [17], [19] and ultimately lead to an impact on the healthcare organization's performance in terms of quality of services. The following hypothesis is formulated.

- BDAC have a positive impact on the domains of healthcare service quality, in terms of structure (H2a), process (H2b), and outcome (H2c).

D. Effects of BDATR on BDAC

The successful employment of BDATR is more than just the consequence of data technologies and procedures employment, it encompasses a larger variety of factors [29], [55]. In this sense, following the RBV theory and specifically considering the capability-building lens, the technological resources represent the "starting point" for ensuring the improvement of the organizational performance, while capability is the capacity to deploy these resources in the most effective way [43], [52]. As a consequence, the main premise for the effective use of BDA is that an organization has invested in all the necessary technological resources [29], [44]. Thus, we devised the following hypothesis.

- BDA technological resources have a positive impact on BDAC (H3).

E. Role of BDAC on the Relationship Between BDATR and the Quality of Healthcare Services' Domains

The role of technological resources is relevant to the effective use of BDA [52]. However, the literature points out that the technological resources themselves could not explain the difference in the success of the use of BDA in organizations with the same technological equipment [30], [52], [54], [63], although technological resources are considered among the most relevant resources that an organization needs to effectively employ BDA [52]. Therefore, the presence of BDAC can be considered as the ground and the boost for BDATR to have an impact on healthcare services [17], [43]. For the aforementioned reasons, we hypothesized the following.

- BDAC mediate the relationship between BDA resources and the domains of healthcare service quality, in terms of structure (H4a), process (H4b), and outcome (H4c).

Fig. 1 shows the research model and the hypotheses that will be tested in the following section.

III. Research Methods

Aiming to test the hypotheses and consequently answer the research questions, in this study we adopted a questionnaire-based methodology. The questionnaire was built on the basis of a deep literature review of the topic of the research. Then it was tested and verified by healthcare professionals. The constructs of the research model are five, namely BDATR, BDAC, quality of the structure (STR), quality of process (PRO), and quality of outcome (OUT). The BDATR is represented by four items that describe the availability of descriptive statistics on informatics tools, information systems up to date for data collection, and the availability of tools to make analysis and visualize data [42], [52], [64]. BDAC is described by the actual use of data to support decision-making, the mindset about the usefulness of data, the willingness to use data, and the performance of their utilization in daily activities [29], [52], [65]. The STR is described by the availability of adequate environments, appropriate medical equipment and devices, and an adequate number of human resources for patient care [28], [66]. The PRO is described by the physicians' willingness to follow the guidelines for the diagnosis and treatment selection phases, the implementation of prevention activities, patients monitoring afterward a treatment, physicians discussing the pros and cons with patients for treatment choice, physicians' willingness to consult and discuss with others physicians before making the decisions [28], [66], [67]. Finally, OUT is described by the outcome obtained by the healthcare organization's activities in terms of the patient's physical well-being and chances of survival, the patient's emotional well-being and quality of life, and patient satisfaction with their living conditions [28], [66]. Table III in Appendix A shows the constructs and the respective items. For each item, a statement was used to understand how strongly the respondent agreed and a Likert scale from 1 (absolutely disagree) to 5 (absolutely agree) was used to measure the healthcare professional perspective. Moreover, the respondents were assured that their personal information would remain confidential. Afterward, the questionnaire was administered through email to the selected sample which consists of healthcare professionals from Italian healthcare organizations (e.g., physicians, medical directors, and general managers). They were selected because they are more likely to objectively assess the current impact of the use of BDA technological resources and capabilities on the quality of healthcare services domains. Moreover, the data analysis was performed using the partial least square structural equation modeling (PLS-SEM) methodology [68]. This approach was chosen because, according to Hair et al. [68], it is more appropriate for small samples and allows for the estimate of complicated models with several constructs, indicator 2 variables, and structural paths without imposing any distributional assumptions on the data [69].

IV. Analysis of Results

We collected a final set of 173 responses from healthcare professionals in Italian healthcare organizations. Following Cohen [70] and Hair et al. [68], the recommended sample size for the PLS-SEM analysis for the model investigated in this article is 110 with a minimum R2 value of 0.10 and a statistical power of 80%, therefore, the study's sample size exceeds the recommended threshold confirming the validity of the sample. Table I shows the characteristics of the sample.

TABLE I
Sample Demographic Characteristics

Demographic characteristics	Number of respondents	Percentage of respondents
Gender		
Female	71	41%
Male	99	57%
Non specifies	3	2%
Experience		
< 5 years	5	3%
Between 5 and 10 years	15	9%
>10 years	153	88%
Role		
Healthcare manager	7	4%
Administrative manager	2	1%
Department manager	4	2%
Operational Unit Manager	88	51%
Physician	67	37%
Nursing coordinator	5	3%

We performed a nonresponse bias test to guarantee the data's validity. Following Werner et al. [71], we investigated the differences between early and late respondents based on the date of receipt of the questionnaire ($N = 83$ and $N = 90$, respectively), and after applying the t-test to the responses of the two subsamples, we discovered no significant statistical difference ($p > 0.05$). As a consequence, we determined that nonresponse is not a major concern in this study. Moreover, we designed and tested the survey, respectively, to reduce and verify the effect of the common method bias, i.e., the bias caused by systematic error variance shared by variables assessed or collected with the same source or technique. First, we applied some procedural remedies in the "survey design" phase to reduce the likelihood that common method bias occurs. In this research, as procedural remedies suggested by Podsakoff et al. [72], we divided the survey into sections for each construct, ensured the respondents' anonymity and privacy, and pretested the survey to eliminate ambiguity in the constructions' items. Second, we tested the common method bias through Harman's single-factor test and Kock's collinearity test [73], [74]. In the single-factor test developed by Harman, the items were subjected to an exploratory factor analysis in which each item was grouped into a single dimension. According to the results, there is not any single factor explaining all of the items' variances, and the first factor did not account for the majority of the variance. Despite the widespread usage of Harman's single-factor test, Podsakoff et al. [72] claimed that it would be reliable only in the case in which one single factor accounts for the majority of the variance demonstrating that there is a common method bias issue. In contrast, Hulland et al. [75] argue that it should never be used by researchers since it is not a reliable test for CMB. Therefore in order to ensure the reliability of our results we turned our attention to a full collinearity test or Kock's collinearity test to examine both vertical and lateral collinearities [74]. In Kock's collinearity test, we checked the variance inflation factors (VIF) for each pair of constructs. In the literature, VIF values are considered acceptable if less than five [76], and in this study all the VIFs were lower than the suggested threshold. Therefore, the results of Kock's collinearity test showed that the common method bias was not an issue in this study.

A. Items and Internal Consistency Reliability

The item's loadings reflect how much of an item's variation is explained by the construct and is known as the variance extracted from the item. Item loadings should be greater than 0.708 because they imply that the construct explains more than half of the variation in the items, resulting in adequate item reliability [69]. All items in this study are above the threshold of 0.708, ensuring the item's reliability. Internal consistency reliability can be defined as the extent to which the items measuring the same construct are associated with each other [68]. To test the internal consistency reliability, we used two measures Cronbach's alpha and composite reliability. The Cronbach's alpha value and composite reliability of 0.7 are considered benchmark values [69]. At this level and higher, the items are sufficiently consistent to indicate the construct is reliable. The results revealed that Cronbach's alpha and composite reliability are all above the 0.7 thresholds for each construct. Table IV in Appendix A shows the items' loadings, Cronbach's alpha, and composite reliability for each construct.

B. Convergent and Discriminant Validity

Convergent validity is demonstrated when measurement items converge to represent the construct itself. The mean of the squared loadings of each item linked with a construct is used to compute the average variance extracted (AVE) and the convergent validity is demonstrated statistically when the AVE is greater than 0.5 [69]. In this study, all constructs have corresponding AVE well above the threshold of 0.5. Table IV in Appendix A shows the AVE for each construct. To determine the distinctness of the constructs in the study, the discriminant validity is determined. It demonstrates that the constructs in the study have their own distinct identities and are not strictly associated with other constructs in the study. To test the discriminant validity, we used the Fornell and Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio [69]. The Fornell and Larcker criterion states that discriminant validity is demonstrated if the square root of AVE for a certain concept exceeds its correlation with all other constructs, while the HTMT ratio value above 0.9 represents a lack of discriminant validity. In this study, both tests demonstrated the discriminant validity between the constructs. Table V in Appendix A shows the results of the discriminant validity tests.

C. Hypotheses Testing

We assessed the model's hypotheses by using the bootstrap resampling method with 5000 iterations to determine the statistical significance of the results. The results of the R2 demonstrated that the model can adequately account for the variation of the constructs, coherently with Cohen [70] and Falk and Miller [77] (R2 for BDA capabilities is 0.161, R2 for STR is 0.270, R2 for PRO is 0.195, and R2 for OUT is 0.259). The predictive validity has been tested through the PLSpredict algorithm on SmartPLS set with 10 folds and 10 repetitions [78]. Specifically, we first checked that the Q2 was greater than 0 for each indicator and it was verified for the vast majority of the indicators (13 out of 16). Accordingly, we then checked that the root mean square error (RMSE) of all the indicators for the PLS-SEM was less than that of the corresponding linear regression model [78], thus demonstrating the predictive validity of the model. Table VI shows the results of the predictive validity analysis. Concerning the hypotheses testing, Table II shows the results of the performed PLS-SEM. In particular, the results showed that the BDATR have a positive and significant direct effect on the STR (H1a), but the direct effect on the quality of process (H1b) and outcome (H1c) was not found significant. BDAC have a positive and significant impact on all the quality of healthcare services domains, namely structure (H2a), process (H2b), and outcome (H2c). Moreover, the direct effect of the BDATR on the BDAC (H3) was found to be positive and significant. It is also interesting to point out that all the mediating hypotheses (H4a, H4b, and H4c) were found positive and significant. In particular, the mediating effect of BDAC between BDATR and the STR is known as complementary mediation, i.e., when the indirect effect is significant (H4a) and the direct effect is positive and significant (H1a) [79], implying that BDAC explain the connections between the independent (i.e., STR) and dependent variables (i.e., BDATR). While the mediating effect of BDAC on the relationship between BDA resources and the quality of process and outcome is found to be a full mediation since the direct effect (H1b and H1c) is not significant whereas the indirect effect (H4b and H4c) is significant. This type of mediation infers that the effect of BDATR on the quality of process and outcome is completely conveyed through the BDAC [79]. Fig. 2 shows the results obtained in the research model. The findings of the study confirm the expected relationships among BDATR, BDAC, and the quality of healthcare services domains, thereby ensuring the nomological validity of the overall research model [80]. Moreover, the "unobserved heterogeneity" was tested in order to ensure the reliability and consistency of the results through

TABLE II
RESULTS OF HYPOTHESES TESTING

Hypotheses	Path coefficient	Standard deviation	T value	P value	Result
H1a: BDATR -> STR	0.256	0.070	3.659	0.000***	Supported
H1b: BDATR -> PRO	0.098	0.077	1.271	0.204	Not Supported
H1c: BDATR -> OUT	0.075	0.068	1.117	0.264	Not Supported
H2a: BDAC -> STR	0.360	0.075	4.792	0.000***	Supported
H2b: BDAC -> PRO	0.393	0.082	4.781	0.000***	Supported
H2c: BDAC -> OUT	0.474	0.080	5.957	0.000***	Supported
H3: BDATR -> BDAC	0.401	0.065	6.188	0.000***	Supported
H4a: BDATR -> BDAC -> STR	0.145	0.044	3.322	0.001***	Supported
H4b: BDATR -> BDAC -> PRO	0.158	0.047	3.335	0.001***	Supported
H4c: BDATR -> BDAC -> OUT	0.190	0.050	3.809	0.000***	Supported

***p<0.01; **p<0.05; *p<0.1

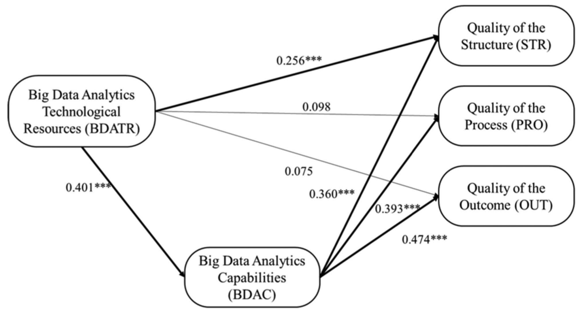

Fig. 2. Research model results.

the use of FIMIX-PLS algorithm. The details and results of the FIMIX-PLS analysis are described in Appendix B.

V. Discussion

In this study, the authors investigated how BDA resources and capabilities influence the quality of healthcare services' domain (i.e., structure, process, and outcome) in the context of healthcare organizations from the perspective of RBV theory. Moreover, the mediating effect of the use of BDAC is proposed and investigated. The findings presented in this study have significant implications for scholars as well as for practitioners' perspectives.

From an academic perspective, in line with the RBV theory, the findings show that the resources represent only the "starting point" and an organization needs to develop the capabilities to effectively deploy these resources [43]. Moreover, to the best of the authors' knowledge, this study is the first to empirically demonstrate the actual impact of BDAC on the quality of service, contributing to the existing literature by providing empirical evidence of the direct relationship between BDAC and the quality of service in healthcare organizations. Also, the study advances the existing knowledge by empirically demonstrating what has been mostly theoretically formulated so far, namely the role of BDATR in strengthening a healthcare organization's quality of services. Infrastructure, technologies, software, data, and other basic resources are considered crucial pillars for success in the context of BDA deployments [52]. The current study found that the presence of BDATR affects positively and significantly only the STR (H1a). Thus, the presence of BDA resources impacts positively only the managerial characteristics of the healthcare quality services' domains, such as the availability of adequate equipment, facilities, and staff dimension, while the positive effect of BDATR on the quality of process (H1b) and outcome (H1c) was not found to be significant. The effect of BDATR on the STR is quite intuitive since the STR is determined by the presence of facilities, equipment, and human resources whose effective use can be monitored by BDATR. Hence, their presence may ensure higher quality. Contrarily, the process and outcome quality are determined by abstract factors (e.g., relationship with patients, and willingness to follow the guidelines). Thus, an effective application of BDATR requires an effort to analyze and interpret data beyond their mere presence. These results point out that the presence of BDATR does not ensure the healthcare services' quality alone, coherently with the RBV theory. This finding suggests the need to develop capabilities to make resources have an impact on the organization's performance [29], [43]. In contrast to the findings for BDATR, the BDAC affect positively and significantly all the domains of healthcare service quality (H2a, H2b, and H2c). This result is perfectly coherent with the academic literature about the RBV theory, pointing out that the capabilities need to be developed to make investments in technological resources relevant to the organization's performance. In this context, capabilities for effectively storing, analyzing, and exploiting data to turn data into insights are relevant for ensuring the quality of service leading to optimal healthcare organization performance [20], [29], [54]. Finally, we tested whether the BDAC could be the underlying mechanism that explains the positive effect of the BDATR on the domains of healthcare service quality. The findings show that the BDAC mediate these relationships but in two different ways. We found that BDAC are one of the explaining mechanisms of the positive relationship between BDATR and STR, while the presence of BDAC is imperative to improve the quality of process and outcome through BDATR.

The findings present also valuable implications to healthcare decision-makers and practitioners interested in the use of BDA in their organizations. This study clarifies the impact of BDAC in enabling the positive effect of BDATR on healthcare service quality domains. This finding suggests healthcare managers and policymakers focus on BDAC development rather than focusing exclusively on the acquisition of BDATR, hence guiding their investment decisions. Considering this perspective, this study could encourage the concurrent investment in BDA technologies and capabilities to effectively improve the performance of healthcare organizations, in terms of quality of services. BDATR provide the foundation for healthcare organizations to effectively utilize BDAC and improve the quality of their services. Additionally, understanding the importance of BDA technological resources, capabilities and quality of healthcare services can help healthcare organizations allocate resources and investments strategically to maximize the impact of BDA on service quality. Besides, the BDAC also need technical skills as well as technological resources to be properly developed [46], [52], [86]. Therefore, the acquisition of BDA technical skills or skilled human resources is now a necessity for healthcare organizations in this technology disruption and digital transformation era [87]. Based on these findings, healthcare managers and policymakers should invest in BDATR alongside BDA technical skills acquisition to develop BDAC in order to have an impact on the quality of healthcare services.

VI. Conclusion

BDA is revolutionizing the healthcare industry and their potential is still not entirely exploited. The amount of investments in BDATR is increasingly growing. These investments aim to improve the quality of healthcare services enabling the support of the decision-making processes of healthcare professionals (e.g., healthcare managers, physicians, and policymakers). However, the effectiveness of BDA seems not guaranteed by the acquisition of BDATR [31], [32], [52]. This study aimed to examine the relationship between BDA technological resources and capabilities with the quality of healthcare services domains (i.e., structure, process, and outcome), and if the presence of BDAC in healthcare organizations can explain the effect of the BDATR on the quality of healthcare services' domains. This study empirically proved that the mere presence of technologies does not lead to an improvement in the quality performance of healthcare services, coherently with the RBV theory. Moreover, the findings show that the presence of BDAC explains the effectiveness of technological resources on the performance of healthcare organizations. This result highlights the necessity to develop BDAC concurrently with investments in technological resources. The academic literature points out that one of the main factors that lead to the development of BDAC is the acquisition of technical skills to properly exploit technological resources. Based on the findings of this study, the mere acquisition of technological resources is not enough for performance improvement, consequently, the acquisition of skilled human resources or the development of skills in this era of digital disruption could be relevant to obtain an organization's performance improvement. While providing an opportunity to further explore the proposed model, this study is not without limitations. First, the cross-sectional rather than longitudinal nature of the data collection means that the generalizability of the results is subject to limitations. Second, this study focuses on the opinions of Italian healthcare professionals, so it might be interesting to examine the proposed model in other countries to identify similarities and differences. Third, despite RBV theory's prominent role in the management research landscape, it adopts a static perspective by assuming that the firm's environment is relatively unchanging [38], [40]. Such a limitation reduces its explanatory power in a rapidly changing environment and requires that dynamic capabilities should be incorporated in order to better explain how organizations can achieve and sustain competitive advantage, as proposed by the dynamic capability view (DCV) theory [43], [45], [88]. DCV theory argues that a firm's ability to adapt and change in response to its environment is a critical source of competitive advantage by effectively mobilizing and reconfiguring its resources and capabilities to take advantage of them [38], [77]. However, the purpose of this study was to empirically evaluate the link among BDA technological resources, capabilities, and the quality of healthcare services rather than explore the ability of these capabilities to adapt to turbulent environments. Future research should adopt the DCV theoretical lens, by considering the dynamic capabilities and by examining the relationship between dynamic capabilities, BDATR, and the quality of healthcare services, as this could provide valuable insights into how healthcare organizations can navigate and respond to changing circumstances and turbulent environments. In addition, examining the role of organizational culture and leadership in facilitating the development and use of dynamic capabilities would further enhance our understanding of the relationship among BDA technological resources, capabilities, and healthcare service quality. Finally, as we did not examine other resources that could have an impact on the quality domains of healthcare services such as the organization's culture, there is room for further investigation on the relationship between BDA resources and capabilities with healthcare quality services domains.

Appendix A

TABLE III
Constructs and Items

Constructs	Items	Indicator	Adapted from
Big Data Analytics Technological Resources (BDATR)	Data are available in the form of descriptive statistics and reports	BDATR1	Benzidia et al., 2021; Dubey et al., 2019; Gupta & George, 2016
	I have easy access to descriptive statistics and reports (e.g., through PC or smartphone)	BDATR2	
	Our information systems are up to date for data collection, storage and management	BDATR3	
	The instrumentation to visualize and use the data is up to date	BDATR4	
Big Data Analytics Capabilities (BDAC)	We use data to support decision making	BDAC1	Ashaari et al., 2021; Gupta & George, 2016; Mikalef et al., 2018
	We believe that collecting, analyzing, and using data is important to our organization	BDAC2	
	We are open to new ideas and approaches based on data as decision support	BDAC3	
	The use of data enables better performance of daily activities	BDAC4	
Quality of the Structure (Str)	There are adequate environments for patient care (inpatient rooms, emergency room environments, operating rooms)	STR1	Donabedian, 1988; Wu and Hsieh, 2015
	Appropriate medical equipment and devices are available for patient care (dressing kits, medicines, instrumentation for invasive and non-invasive operations)	STR2	
	An adequate number of staff is employed for patients care	STR3	
Quality of the Process (Pro)	Physicians follow guidelines for making the diagnosis	PRO1	Donabedian, 1988; Santry et al., 2020
	Physicians follow guidelines for treatment selection	PRO2	
	Prevention activities are carried out to protect the health and safety of the community and patients (e.g., from infectious risks or unhealthy lifestyles)	PRO3	
	Physicians perform patient monitoring activities following an intervention or prescription of therapy	PRO4	
	Physicians discuss the pros and cons with patients for treatment choice	PRO5	Donabedian, 1988; Wu and Hsieh, 2015
	Physicians are willing to consult and discuss with other physicians before making decisions	PRO6	
Quality of the Outcome (Out)	The activities carried out by my healthcare organization improve the patient's physical well-being and chances of survival	OUT1	Donabedian, 1988; Wu and Hsieh, 2015
	The activities carried out by my healthcare organization improve the patient's emotional well-being and quality of life	OUT2	
	The activities carried out by my healthcare organization make it possible to improve patient satisfaction with their living conditions	OUT3	

TABLE IV
LOADINGS, INTERNAL CONSISTENCY RELIABILITY, AND CONVERGENT VALIDITY

Construct	Items	Loading	CR	Cronbach's alpha	AVE
BDATR	BDATR1	0.836	0.871	0.869	0.718
	BDATR2	0.873			
	BDATR3	0.843			
	BDATR4	0.837			
BDAC	BDAC1	0.695	0.840	0.838	0.678
	BDAC2	0.900			
	BDAC3	0.849			
	BDAC4	0.835			
STR	STR1	0.897	0.874	0.837	0.753
	STR2	0.918			
	STR3	0.784			
PRO	PRO1	0.852	0.910	0.902	0.671
	PRO2	0.858			
	PRO3	0.771			
	PRO4	0.801			
	PRO5	0.806			
	PRO6	0.824			
OUT	OUT1	0.873	0.885	0.872	0.794
	OUT2	0.889			
	OUT3	0.911			

TABLE V
DISCRIMINANT VALIDITY

Constructs	BDATR	BDAC	STR	PRO	OUT
Fornell-Larcker criterion					
BDATR	0.847				
BDAC	0.401	0.823			
STR	0.401	0.463	0.868		
PRO	0.259	0.432	0.547	0.819	
OUT	0.266	0.503	0.476	0.557	0.891
HTMT ratio					
BDATR	-				
BDAC	0.452	-			
STR	0.466	0.532	-		
PRO	0.278	0.486	0.619	-	
OUT	0.303	0.575	0.560	0.622	-

TABLE VI
PREDICTIVE VALIDITY

Items	Q^2predict	PLS-SEM_RMSE	LM_RMSE
OUT1	0.043	0.747	0.754
OUT2	0.051	0.858	0.871
OUT3	0.029	0.813	0.821
PRO1	0.029	0.847	0.914
PRO2	0.026	0.813	0.874
PRO3	0.078	0.857	0.892
PRO4	0.039	0.920	0.905
PRO5	-0.009	0.862	0.862
PRO6	-0.004	0.863	0.865
BDAC1	0.001	0.835	0.821
BDAC2	-0.004	0.776	0.769
BDAC3	0.236	0.986	0.947
BDAC4	0.074	0.724	0.721
STR1	0.115	1.076	1.090
STR2	0.134	0.913	0.927
STR3	0.080	1.163	1.171

TABLE VII
FIMIX-PLS ANALYSIS FOR UNOBSERVED HETEROGENEITY

	Number of Segments		
Criteria	**1**	**2**	**3**
AIC	1811.729656	1758.312726	**1718.075**
AIC3	1822.729656	1781.312726	**1753.075**
AIC4	1833.729656	1804.312726	**1788.075**
BIC	1846.415864	1830.838433	**1828.44**
CAIC	1857.415864	**1853.838433**	1863.44
HQ	1825.801641	1787.735966	**1762.849**
MDL5	2073.160694	2304.941259	2549.901
LnL	**-894.8648281**	-856.1563629	-824.037
EN	**0**	0.49508727	0.659301
	Segments		
N° of segments	**1**	**2**	**3**
2	90 out of 173 (52.02%)	83 out of 173 (47.98%)	-
3	92 out of 173 (53.18%)	68 out of 173 (39.31%)	13 out of 173 (7.51%)

APPENDIX B

The unobserved heterogeneity refers to the acknowledgement that individuals and organizations, used as study samples in structural model analysis, may differ in behavior and structure [81], [82]. Therefore, the traditional assumption of a single homogeneous population, as often made in studies using PLS-SEM, is considered unrealistic [83]. Neglecting the heterogeneity test, as underscored by other scholars [84], [85], poses a threat to result validity and may lead to misleading conclusions. For these reasons, the unobserved heterogeneity was tested using the FIMIX-PLS module in the SmartPLS 4.0.9.9 and by following the steps presented in [81]. Table VII shows the results of the FIMIX-PLS analysis to test the unobserved heterogeneity with an active dataset of 173 respondents. The first step is the identification of the maximum number of segments following the recommendations of Hair et al. [82]. Therefore, a G-power analysis was conducted (alpha $=$ 0.05, power $=$ 0.80, and effect size 0.15) to estimate the minimum sample size, which yielded 55. The greatest integer from dividing the sample size (i.e., 173) by the minimum sample size (i.e., 55) yields a theoretical upper bound of 3 segments. The analysis was conducted for a one-segment, two-segment, and three-segment solutions with the settings for the maximum number of iterations (5000), stop criterion ($1 \cdot 10\text{-}9 = 1.0\text{E-}10$), and the number of repetitions (10). Following the recommendations of Matthews et al. [81], the criteria analysis among the results with different segments pointed out the 3-segment solution as the most reliable one. However, the relative segment sizes show that the segment 3 of the 3-segment solution is too small (7.51%) for a segment-specific PLS-SEM analysis, thus, selecting more than two segments is not reasonable [85]. Considering the 2-segment solution, the normed entropy statistic (EN) is under the threshold of 0.5, suggesting that the segments are not well-separated [82]. Therefore, it is reasonable to conclude that there is no substantial level of heterogeneity in the data [81], [82].

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Luigi Jesus Basile received the Ph.D. degree in mechanical and management engineering from the Polytechnic University of Bari, Bari, Italy, in 2023.

He has conducted research as a Research Fellow with the Polytechnic University of Bari in areas such as risk management approaches for critical infrastructure, digital transformation strategies, and the utilization of business intelligence to support physicians and policymakers in healthcare. He has been a Visiting Scholar with the Institut Mines Telecom Business School (Evry, FR). He is the author of international peer-reviewed publications on the theme of digital transformation in healthcare, which is his main research interest, alongside healthcare management, industry 4.0, and supply chain risk management.

Nunzia Carbonara received the Ph.D. degree from the Department of Industrial Engineering and Management Sciences, Politecnico di Bari, Bari, Italy, 1998.

She is currently a Full Professor of Strategic Management and Organization, Politecnico di Bari, and a Coordinator of the Management Engineering Bachelor's Programme. She has authored or coauthored premier and academic journals on the topics of her research interests, which include corporate strategies and organization, innovation management in public procurement, public private partnerships, and the effect of digital transformation on organizations and business models. She coordinates and is involved in several funded international and national research projects on her research topics.

Dr. Carbonara is a Member of the editorial board for the *Journal of Risk and Financial Management* and *Journal of Business and Management*.

Umberto Panniello received the Ph.D. degree in management engineering from Politecnico di Bari, Bari, Italy, in 2010. He is currently an Associate Professor of E-Business Models and Business Intelligence, Politecnico di Bari. He has been a Visiting Scholar with the Wharton Business School, University of Pennsylvania, Philadelphia, USA, and with the Financial University under the Government of the Russian Federation, Mosca, Russia, and a Distinguished Visiting Scholar with the Beijing Normal University, Beijing, Cina. His current main research interests are digital transformation, business model innovation, metaverse, and space economy. He has also done research on knowledge discovery in databases to support decision-making process.

Prof. Panniello is an Associate Editor for the *Technology Analysis & Strategic Management*, and he is on the Editorial Board for the *Journal of Knowledge Management*. He is the author of journal articles (appearing in outlets such as *Information System Research*, *Journal of Product Innovation Management*, *Technovation*, and *Technological Forecasting and Social Change*), books, and conference proceedings.

Roberta Pellegrino received the Ph.D. degree in management engineering from Politecnico di Bari, Bari, Italy, in 2010.

She is currently an Associate Professor in Management Engineering with Politecnico di Bari. She has been a Teacher for several master's courses or Ph.D. lecturers on the themes of risk management, PPP, and real option theory. She has been a Visiting Scholar with Columbia University, New York, USA. She is the author of more than 50 publications in international journals and books, and more than 70 papers presented at international and national conferences. Her main research interests are public-private partnership (PPP), supply chain risk management, real options theory, and other topics in the field of economic-management engineering. She coordinates and is involved in research projects with companies and other private/public organizations.

Dr. Pellegrino is a Member of the ISCRIM network (Supply Chain Risk Management Network) and has been a Member of the European project European Cooperation in the field of Scientific and Technical Research - COST - "Public Private Partnerships in Transport: Trends and Theory" since 2010.