MASTER'S THESIS

The mediating role of innovation ambidexterity on big data analytics capability and patient service performance

Meulenkamp, C.

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Student:	Chanel Meulenkamp
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Thesis supervisor	Rogier van de Wetering
Second reader	Pien Walraven
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Preface

Over the past few years, the confluence of several trends in the health industry has accelerated. In particular, consumers have a growing need for convenience and easily accessible health care. To cater to those needs, digital transformation is considered by leading health systems as a way to become more consumer-friendly while simultaneously changing their operations, culture, and use of technology.

Healthcare providers have high levels of ambition for digital optimization and transformation. However, their aspirations are hindered by a significant gap in their innovation ambidexterity capabilities. Innovation ambidexterity is considered finding a balance between exploitative and explorative innovation activities.

This research contributes to the scientific literature on digital transformations within healthcare. It examines a new conceptual framework using survey data of Dutch hospital departments and employing structural equation model (SEM) analysis from the partial least square (PLS) approach. This research is one of the first studies that show the effects of big data analytics capability, evidence-based decision-making culture, and innovation ambidexterity on patient service performance. Besides that, it also fills the literature gaps related to driving factors of digital innovation and the mediating role of innovation ambidexterity on patient service performance.

<u>Key terms</u>

Big data analytics capability, evidence-based decision-making culture, innovation ambidexterity, patient service performance, quality of care, and hospital departments.

Summary

Digital technologies have great potential to transform global health systems to be more accessible, affordable, scalable, and fit-for-purpose. In addition, numerous public health systems are currently reinventing themselves, and digital technologies are playing an increasingly important role in their transformations. Innovative technologies can contribute to ensuring hospitals can continue to operate while at the same time enhancing the quality of care. Research reveals that hospitals do have high ambitions for digital optimization and transformation. However, their aspirations are hindered by a significant gap in their innovation ambidexterity capabilities to execute. To obtain digital optimization and transformation, hospitals are required to find a balance between exploitative and explorative innovation activities.

Enabling both explorative and exploitative activities can be particularly complex. While exploitation refers to refinement and efficiency, exploration is related to discovery and searching. Previous research has shown that organizations can benefit from developing an analytic capability that enables establishing risk models and dashboards based on high-quality data. This research offers insights into how hospitals might innovate care delivery using dynamic capabilities such as big data analytics capability and evidence-based decision-making culture.

Based on the theory, four hypotheses have been formulated:

- H1: A hospital department's big data analytics capability positively affects innovation ambidexterity.
- H2: A hospital department's big data analytics capability does not directly affect the patient service performance of a hospital department.
- H3: An evidence-based decision-making culture positively affects the relationship between the data analytics capability of a hospital department to achieve innovation ambidexterity.
- H4: The higher the level of innovation ambidexterity in a hospital department, the higher the level of service performance.

From September 2021 till December 2021, the hypotheses have been tested utilizing survey research among Dutch hospitals. Through convenience sampling, respondents were voluntarily contacted by email, social media, or telephone. After the data cleaning, 107 usable surveys were subsequently analyzed using the PLS-SEM method in the tool SmartPLS. Therefore, the quality of the measurement model is determined with path model loadings, internal consistency reliability, convergent validity, discriminant validity, and structural model evaluation. After these checks, the data turned out to be valid and reliable.

Results of the survey show that a hospital department's big data analytics capability positively affects innovation ambidexterity. Furthermore, the effect of big data analytics capability does have a direct effect on patient service performance. However, this is very low. An interesting outcome was the results of evidence-based decision-making culture; it does have a positive effect, only not on the construct thought beforehand. This research has confirmed that innovation has a significant role to play in increasing patient service performance and, therefore can help hospitals to enhance the quality of care.

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1. Introduction

1.1. Background

Over the past few years, the confluence of several trends in the health industry has accelerated. In particular, consumers have a growing need for convenience and easily accessible health care. To cater to those needs, digital transformation is considered by leading health systems as a way to become more consumer-friendly while simultaneously changing their operations, culture, and use of technology (Appleby et al., 2021). According to Allen (2022), digital technologies have great potential to transform global health systems to be more accessible, affordable, scalable, and fit-for-purpose. In addition, numerous public health systems are reinventing themselves accelerated by the COVID-19 pandemic, and digital technologies play an increasingly important role in their transformations.

Hospitals enhance and complement the efficiency of different components in the healthcare system. According to the World Health Organization WHO (2021, p. 111), they provide continuous services for acute and complex conditions. Outside influences and deficiencies in healthcare systems and hospital sectors create a new vision within hospitals. Additionally, an appropriately developed hospital environment increases the effectiveness of health care delivery and enhances the well-being of patients and hospital staff (WHO, 2021).

To meet the need for universally available patient information and better care standards, hospitals have to embrace advanced information technologies like electronic medical reports, artificial intelligence, and big data analytics (Taylor, 2020; van de Wetering, 2018, 2021a; Van de Wetering & Versendaal, 2021). This indicates that hospitals are on the verge of a digital transformation (Van de Wetering, 2021a, 2021c).

The results of Gilbert (2018) reveal that healthcare providers have high levels of ambition for digital optimization and transformation. However, their ambitions are hindered by a significant gap in their innovation ambidexterity capabilities. Innovation ambidexterity is considered finding a balance between exploitative and explorative innovation activities.

Big data analytics (use of advanced analytic techniques against large, diverse big data sets) fulfills a crucial role in the hospital practice to facilitate both explorative and exploitive innovation and achieve innovation ambidexterity (Foglia, Ferrario, Lettieri, Porazzi, & Gastaldi, 2019; Wang & Hajli, 2017; Wang, Kung, Gupta, & Ozdemir, 2019). In addition, an evidence-based decision-making culture can influence the impact of big data analytics capability (BDAC) and the extent to which innovation ambidexterity can be applied (Davenport, Harris, & Morison, 2010; Wang et al., 2019).

The positive effect of an evidence-based decision-making culture on big data analytics capability has been confirmed in previous research. Therefore, it indirectly confirms the same effect for innovation ambidexterity. This research focuses on how hospitals use the two aforementioned digital information technologies to effectively balance paradoxical innovation capabilities to continuously improve the quality of care (patient service performance). To explain the above-mentioned key terms further, the following two pages give insight into the standard definitions of this research.

1.1.1. Big Data Analytics Capability (BDAC)

The concept of big data is commonly described with the three, five, and even seven v's. The seven v's (that expand the scope of the previous three and five v's) are (1) volume, (2) velocity, (3) variety, (4) veracity, (5) virtual, (6) variability, and (7) value (Mathes, 2016, pp. 15-17).

In general, big data analytics refers to "organizational facility with tools, techniques, and processes that enable a firm to process, organize, visualize, and analyze data, thereby producing insights that enable data-driven operational planning, decision-making, and execution" (Srinivasan & Swink, 2018, p. 1851). In the healthcare industry, big data analytics enables to collect, store, analyze, and immense process volume, variety, and velocity of health data across a wide range of healthcare networks to enhance data-driven decision-making and discover business values and insights (Wang et al., 2019; Yu, Zhao, Liu, & Song, 2020). Through big data analytics, hospitals can apply various data visualization analytical tools (e.g., interactive dashboards and systems) to extrapolate meaning from external health data and perform visualization of the information (Wang & Hajli, 2017; Yu et al., 2020). In addition, it enables various analytical techniques (e.g., statistical methods and optimization) to process large amounts of health data in various forms (e.g., text-based health documents, doctors' written notes and prescriptions, and medical imaging) for harvesting business insights (Wang et al., 2019). The visualization reports generated from real-time data processing can be displayed on healthcare performance dashboards, which support the daily tasks of healthcare delivery providers (such as doctors and nurses), thereby enabling them to make smarter, faster data-driven decisions (Wang et al., 2019; Yu et al., 2020). Big data analytics capability is the competence that provides valuable insights using the abovementioned capabilities and transforms a business into a competitive force (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016).

1.1.2. Evidence-Based Decision-Making Culture (EDMC)

Organizational culture plays a vital role in enabling an organization to create business value with analytics (Wang et al., 2019). It is defined as a set of collective values, beliefs, norms, and principles that guide organizations by defining appropriate behavior for various situations (Ravasi & Schultz, 2006). According to Wang et al. (2019), many studies have shown that organizational culture is a significant obstacle to evidence-based decision-making e.g., (Kiron & Shockley, 2011; LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011). Shifting the decision-making process from intuitive thinking and individual experience to 'the facts' facilitated by BDA is a challenge that organizations undertake (Wang et al., 2019). Davenport et al. (2010) describe an evidence-based decision-making culture as an aspect of organizational culture from a big data analytics perspective; a culture of embracing evidence-based management and embedding evidence-based decision-making in the core values and processes of the organization.

1.1.3. Innovation Ambidexterity (IA)

Innovation ambidexterity is a complex dynamic capability. A dynamic capability can be described as a specific capability that enables organizations to rapidly adapt to changing environments and sustain competitive advantage. They are critical to an organization's long-term success (Smith, 2005; van de Wetering, 2021b; Winter, 2003). Innovation ambidexterity has been characterized as the firm's "learning-to-learn" ability which can be managed to promote the sensing and seize of new opportunities and mitigate possible effects of path-dependence (O'Reilly III & Tushman, 2013; O'Reilly III & Tushman, 2008). Innovation ambidexterity refers to finding a balance between exploitative (using current knowledge for improving, e.g., the patient service performance) and explorative (using new knowledge for improving, e.g., the patient service performance) innovation activities (Foglia et al., 2019; Gibson & Birkinshaw, 2004; J. J. Jansen, Tempelaar, Van den Bosch, & Volberda, 2009; J. J. P. Jansen, Van Den Bosch, & Volberda, 2006).

Exploration and exploitation innovation require fundamentally different and inconsistent architectures and competencies that create paradoxical challenges. Whereas exploration has been associated with flexibility, decentralization, and lose cultures, exploitation has been related to efficiency, centralization, and tight cultures (Benner & Tushman, 2003; Foglia et al., 2019). Achieving innovation ambidexterity creates paradoxical situations because the short-term effects of exploitative components conflict with the long-term experimental focus and decentralized architectures of exploratory units (Božič & Dimovski, 2019; Floyd & Lane, 2014). When differentiating exploratory and exploitative efforts, organizations need to establish specific integration mechanisms to coordinate and integrate operational capabilities developed at spatially dispersed locations. Thus, to unravel these paradoxical situations, the mobilization, integration, and deployment of operational capabilities at exploratory and exploitative units is necessary for appropriating value and achieving ambidexterity (Božič & Dimovski, 2019; Foglia et al., 2019; J. J. Jansen et al., 2009).

1.1.4. Patient Service Performance (PSP)

A strategic map of the balanced scorecard (BSC) developed by Kaplan and Norton (2004) defines four perspectives. This method provides executives with a comprehensive framework that translates an organization's strategic objectives into a coherent set of measures. In its original design, the BSC includes performance measures from four interrelated perspectives: (1) financial, (2) internal business process, (3) customer, and (4) learning and growth (Kaplan & Norton, 2004). Van de Wetering, Batenburg, Versendaal, Lederman, and Firth (2006) transformed the original perspectives of the BSC into perspectives that are consistent with hospital strategies:

1. Clinical business process, as a translation of the internal business process perspective;
2. Patient, as a translation of the customer perspective;
3. Quality and transparency, as a translation of the financial perspective;
4. Information systems, as a translation of the learning and growth perspective.

1.2. Problem statement

As mentioned in Paragraph 1.1, according to the WHO (2021), an appropriately developed hospital environment increases the effectiveness of health care delivery. It enhances the well-being of patients and hospital staff (WHO, 2021). Additionally, integrating digitalization through digital transformation is a way to overcome exhaustive management, regulatory and administrative processes that are paralyzing and slowing down hospitals, causing lower service levels and overall quality of care (Van de Wetering & Versendaal, 2021).

Nine years ago, Gastaldi and Corso (2012) already foresaw the emergence of improvement. The results of the digitalization efforts accomplished within the domain of healthcare often fell below expectations: most hospitals gave healthcare digitalization barely a second thought as a source of innovation (Brynjolfsson & Saunders, 2009) and did not adequately analyze the organizational changes required to make all the benefits associated with the digitalization become a reality (Agarwal, Gao, DesRoches, & Jha, 2010). Recent research results of Gilbert (2018) and Taylor (2020) reveal that healthcare providers have a high ambition for digital optimization and transformation. However, their ambitions are hindered by a significant gap in their innovation ambidexterity capabilities to execute and their frequently overlapping optimization and transformation efforts. Research shows that hospitals must find a balance between exploitative and explorative innovation activities (Božič & Dimovski, 2019; Foglia et al., 2019; J. J. Jansen et al., 2009). Bygstad and Øvrelid (2020) imply that this requires ongoing negotiation between conflicting forces. At this time, it is still not clear how hospital departments can implement innovation assets and practices such as innovation ambidexterity to increase patient service performance (Van de Wetering, 2021a). According to Gibson and Birkinshaw (2004) and S. Khin and T. C. F. Ho (2019) innovation ambidexterity stands for the presence of qualities and competencies to manage innovative digital technologies to enhance the patient service performance (according to the three perspectives patient relationship, service attribute, and hospital image of Wu and Hu (2012)).

Enabling explorative and exploitative activities can be particularly complex (Foglia et al., 2019; Lavie, Stettner, & Tushman, 2010). While exploitation refers to refinement and efficiency, exploration is related to discovery and searching (Foglia et al., 2019; March, 1991). Previous research has shown that organizations with a big data-driven culture are more likely to derive the full benefits of big data initiatives (Bygstad, Øvrelid, Lie, & Bergquist, 2019; Dubey et al., 2019; Yang & Hsiao, 2009). According to Ghosh and Scott (2011) and (Yu et al., 2020), many organizations can benefit from developing an analytic capability that enables establishing risk models and dashboards based on high-quality data. These models facilitate measurable impacts (e.g., decision-making). Additionally, the value of big data analytics is not only in generating insight; the true potential is where the insight is followed (Mikalef, van de Wetering, & Krogstie, 2020; Wang et al., 2019). In conclusion, this research offers insights into how hospitals could utilize dynamic capabilities such as big data analytics capability and evidence-based decision-making culture to enhance the quality of care.

1.3. Research objective and questions

With this in mind, and in line with the focus of the hospital industry to enhance the quality of care while simultaneously changing their operations, culture, and use of technology. This research acclaims that a big data analytics capability and evidence-based decision-making culture increase the ability to perceive and respond satisfactorily to the consumer's growing needs by enabling innovation ambidexterity (Van de Wetering, 2021a). Thereby, this research follows a practitioner-based approach (Bhattacherjee, 2012; Saunders, Lewis, Thornhill, & Pearson, 2019; Verschuren & Doorewaard, 2021). This research focuses on the department level and service performance of Dutch hospitals. Therefore, it can be considered the degree to which a hospital department can 'explore' and 'exploit' big data analytics and evidence-based decision-making to improve the patient service performance and, ultimately, the quality of care.

Therefore, this research seeks to address the following research questions:

Q1: What is the role of the big data analytics capability in applying innovation ambidexterity to the patient service performance of a hospital department?

Q2: What effect has an evidence-based decision-making culture on a hospital department's big data analytics capability to achieve innovation ambidexterity?

Q3: What is the effect of innovation ambidexterity on the patient service performance of a hospital department?

This research contributes to the scientific literature on digital transformations within healthcare by addressing the challenges above and unraveling innovation ambidexterity to improve patient service performance in hospital departments. Therefore, hospitals can respond to digital transformations and meet the quality of care demands.

1.4. Main lines of approach

This research is structured in the following way: first, it reviews the theoretical development in which the primary literature on big data analytics capability (BDAC), evidence-based decision-making culture (EBDMC), innovation ambidexterity (IA), and patient service performance (PSP) is highlighted. Furthermore, this chapter also underlines this study's research model and associated hypotheses. Chapter three emphasizes the methods used in this research, after which chapter four outlines the research' results. This research document ends by discussing the outcomes, including theoretical and practical contributions, and ends with concluding remarks.

2. Theoretical framework

This chapter provides a theoretical framework that will form the basis for empirical research.

2.1. Research approach

This research aims to answer the research questions mentioned in Paragraph 1.3. To answer the abovementioned questions and find relevant literature, two methods are used; the snowballing method (Wohlin, 2014) and the building blocks method (Van Veen & Westerkamp, 2008).

2.1.1. Snowballing method

The snowballing method starts with identifying a tentative start set of articles and evaluating these for inclusions and exclusions. Snowballing consists of two parts; backward and forward snowballing. Backward snowballing means using the reference list of the selected articles to identify new articles to include. Forward snowballing refers to identifying new articles based on those citing the article being examined (Wohlin, 2014). From the master's program, there are already several articles that have been provided. The following articles are selected as input for the snowballing method (see table 1), covering all elements of the research questions.

Title article	**Reason why selected**
1. Architectural alignment of process innovation and digital infrastructure in a high-tech hospital (Bygstad & Øvrelid, 2020)	Recent article, hospital environment (case study), digitalization, and digital innovation.
2. What drives hospital wards' ambidexterity: Insights on the determinants of exploration and exploitation (Foglia et al., 2019)	A recent article, hospital wards (quantitative research with 80 complete responses), ambidexterity: exploration and exploitation.
3. The antecedents, consequences, and mediating role of organizational ambidexterity (Gibson & Birkinshaw, 2004)	Ambidexterity in an organizational environment, and quantitative research with 4195 respondents from 41 business units.
4. Exploratory innovation: exploitative innovation, and performance: effects of organizational antecedents and environmental moderators (J. J. P. Jansen et al., 2006)	Exploratory and exploitative innovation, organizational environment, quantitative research with 283 respondents, found a positive relationship between the extent of rules and procedures within organizational units and exploitative innovation.
5. Leveraging big data analytics to improve quality of care in healthcare organizations:	A recent article, big data analytics, healthcare organizations, evidence-based decision-making

Title article	Reason why selected
A configurational perspective (Wang et al., 2019)	culture, and quantitative research with 63 complete respondents.
6. Examining knowledge management enabled performance for hospital professionals: A dynamic capability view and the mediating role of process capability (Wu & Hu, 2012)	Healthcare sector, patient performance, and quantitative research with 144 respondents.

Table 1: Selected articles as input for Snowballing method

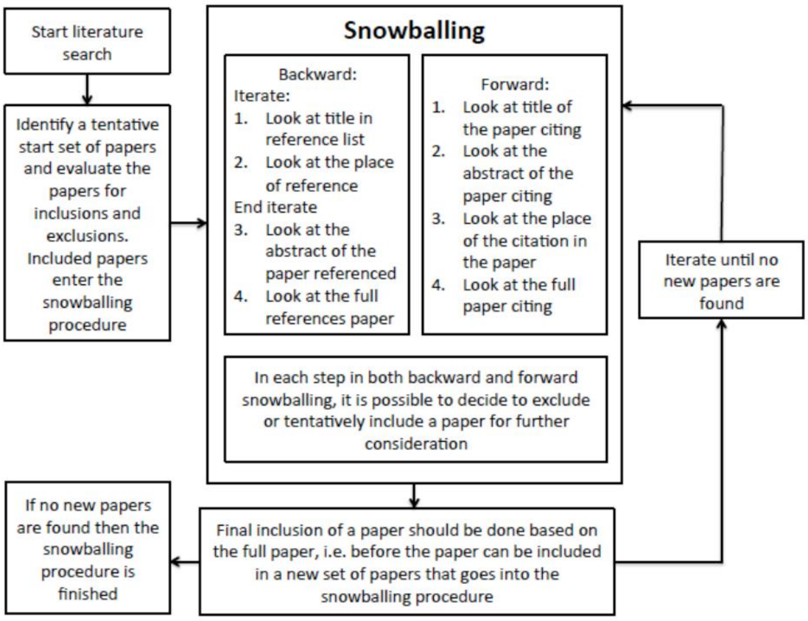

Figure 1: Snowballing procedure (Wohlin, 2014)

As shown in figure 1, the snowballing method starts with selecting articles and follows into conducting ‘backward’ and ‘forward’ snowballing. The third step is the ‘final inclusion’ of an article. The ‘backward’ and ‘forward’ snowballing steps will be relaunched until no new articles are found. Once no new articles are found, the snowballing procedure is finished (Wohlin, 2014). The following paragraph describes the outcomes of the snowballing method.

2.1.2. Building blocks method

The search query will be divided into elements (box diagram). This method aims to find as much relevant literature as possible (Van Veen & Westerkamp, 2008). As a preparation, the main research questions are written down, and relevant ‘elements’ were selected as input for the building blocks method. All research questions have similar elements. Therefore, all elements of the research questions are combined into one building block model. When designing the building blocks model, it is essential to use only synonyms and/or terms with the same meaning (Van Veen & Westerkamp, 2008). To ensure that all relevant literature is found, queries with up to three parts of the building blocks are performed in addition to the complete query.

Selection of relevant research questions’ elements:

Q1: What is the role of the big data analytics capability in applying innovation ambidexterity to the patient service performance of a hospital department?

Q2: What effect has an evidence-based decision-making culture on a hospital department's big data analytics capability to achieve innovation ambidexterity?

Q3: What is the effect of <u>innovation ambidexterity</u> on the <u>patient service performance</u> of a <u>hospital department</u>?

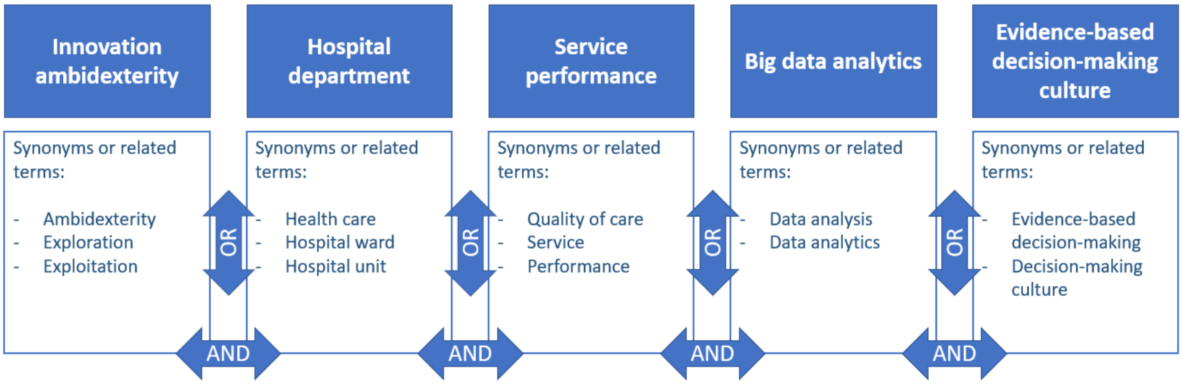

Figure 2: Building blocks method Q1, Q2, and Q3

The building blocks of figure 2 result in the following query for all research questions combined: TS=("innovation ambidexterity" OR "ambidexterity" OR "exploration" OR "exploitation") AND TS=("hospital department" OR "health care" OR "hospital ward" OR "hospital unit") AND TS=("patient service performance" OR "quality of care" OR "service" OR "performance") AND TS=("big data analytics" OR "data analysis" OR "data analytics") AND TS=("evidence-based decision-making culture" OR "evidence-based decision-making" OR "decision-making culture")

2.1.3. Online databases and search engines

To ensure maximum coverage in the literature search, the following relevant online databases and search engines will be used (see table 2). The selection is based on the information provided by the Open University Library (Saunders et al., 2019).

Name of database/search engine	**Relevant information about database/search engine**
1. Open University database	Database of the Open University, which has access to several other databases.
2. Academic Search Elite (EBSCO)	Multidisciplinary database containing the full text and abstracts of over 2,100 scholarly journals, of which over 1,700 are peer-reviewed. Contains journals, periodicals, reports, and books.
3. Business Source Premier (EBSCO)	International economic research database with over 2200 full-text journals, including the top management and marketing journals such as Journal of Marketing, Harvard Business Review, Fortune, and Time Magazine.
4. Google Scholar (especially relevant for forward snowballing)	Google Science is a search engine that searches a growing collection of scientific publications from academic publishers, professional organizations, universities, and other scientific organizations.

Table 2: Selected online databases and search engines

2.1.4. Selection criteria and reading perspective

The following criteria will be applied when searching literature (Saunders et al., 2019):

- Assessing criteria:
    - Research scope: Big data analytics, evidence-based decision-making culture, innovation ambidexterity, quality of care, patient service performance, and hospital departments;
    - Title: relevant to the research scope.
- Assessing value:
    - Scholarly (peer-reviewed) journals;
    - Language of publication: English and Dutch;
    - Published date starting at 2010.

To determine the relevance and value of the literature found, a reading perspective consisting of five critical questions of Wallace and Wray (2021) is applied. "Those questions are specific questions you ask of the reading, which will be linked either directly or indirectly to the research questions" (Saunders et al., 2019).

2.2. Implementation

The following description contains the results and the most relevant references resulting from the searching methods. Several applications are used to perform the literature review as comprehensibly and methodically as possible. EndNote is a reference management tool in which all references and associated files are stored (if found relevant during the literature search. In addition, a logbook (.xlsx file) was created to record all references and numbers as accurately and thoroughly as possible.

2.2.1. Outcome snowballing method

Tables 3 and 4 show the results of the snowballing method. Google Scholar and the Open University library were used for the entire snowball method. Google Scholar shows all the articles that have cited a particular article, which is required to perform the forward snowballing method.

Backward snowballing

Description	Result
Number of articles to which backward snowballing has been applied	23
Number of references in the articles	1309
Number of relevant articles based on the title	124
Number of selected articles based on content	79

Table 3: results backward snowballing method

Forward snowballing

Description	Result
Number of articles to which forward snowballing has been applied	6
Number of relevant cited articles based on the title	23
Number of selected articles based on content	12

Table 4: results forward snowballing method

2.2.2. Outcome building blocks method

For the building blocks method, selected search engines are used, criteria, and developed queries (see Paragraph 2.1). Unfortunately, the entire query results in few or no results by the selected search engines and online databases. Either 'SmartText Searching' is applied with suggestions, or no result is shown. For this reason, the building blocks were divided and then entered into the databases. As shown in table 5, results are demonstrated, however, very specifically on one component only. Conclusion: the existing literature is very scarce concerning the chosen research topics. On the other hand, there is enough information on each topic. In Paragraph 2.3, the found literature will be processed.

Description	**Result**
Search engines used	Open University database, Academic Search Elite (EBSCO), Business Source Premier (EBSCO), and Google scholar.
Number of search results	1875
Number of selected articles based on content	15

Table 5: total results building blocks method

2.3. Results and conclusions

This paragraph sets out the theoretical framework developed for this research. First, the answers and arguments to the research questions found in the literature will be described in the theoretical framework. This is followed by a list of conclusions of the theoretical framework for the remainder of the research. Figure 3 shows the research model and the related hypotheses explained below.

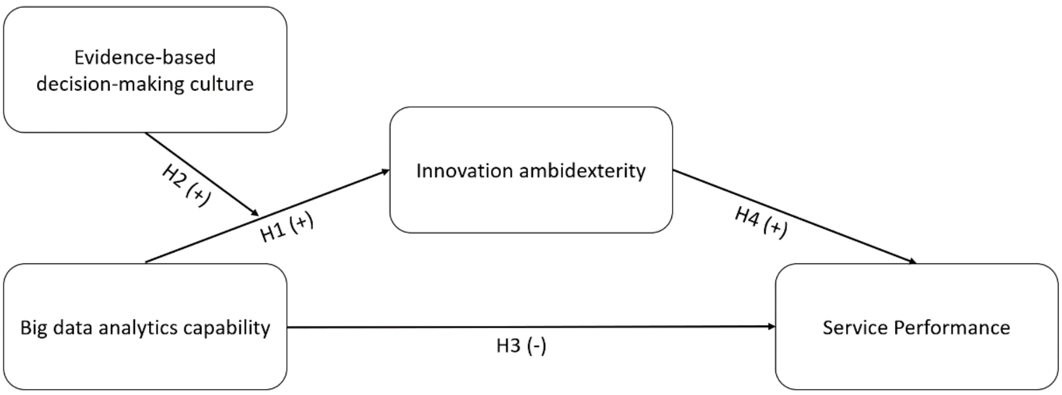

Figure 3: Research model

According to S. Khin and T. C. Ho (2019), digital dynamic capabilities can be described as the "organization's skill, talent, and expertise to manage digital technologies for new product development." Van de Wetering (2021a) acknowledges this definition and states that a dynamic capability is crucial for a hospital department to adopt digital technologies, stimulate digital transformations, and evolve innovative services and products that increase patient service performance. With this in mind, a hierarchical capability view is adopted in this research (Božič & Dimovski, 2019; Van de Wetering, 2021a).

<u>Big data analytics capability and innovation ambidexterity</u>

A big data analytics capability can be conceptualized as a digital dynamic capability (Van de Wetering, 2021a). This capability is considered a lower-order technical dynamic capability that enables evolving higher-order dynamic organizational capabilities such as innovation ambidexterity (Van de Wetering, 2021a; Yu et al., 2020). According to Van de Wetering (2021a), a digital dynamic capability is essential to innovate and improve business operations using digital technologies. These digital technologies involve big data analytics and artificial intelligence. A digital dynamic capability can be described as an organization's ability to stimulate digital transformations and evolve innovative services and products that increase patient service performance. The research of Van de Wetering (2021a) and Yu et al. (2020) identified a big data analytics capability as a digital dynamic capability. In addition, it showed that this capability is required to affect a dynamic organizational capability such as innovation ambidexterity positively. In this research, we are examining the particular role of the big data analytics capability in applying innovation ambidexterity as a mediator to the patient service performance of a hospital department. Therefore, the following hypothesis is defined:

Hypothesis 1: A hospital department's big data analytics capability positively affects innovation ambidexterity.

<u>Big data analytics capability's role within hospital departments on patient service performance</u>
Mikalef et al. (2020) and Wang, Kung, and Byrd (2016) highlight that realizing business value from big data analytics contains five characteristics. In summary, this means a certain maturation level and continuous improvement cycles in learning and adapting, translating big data analytics into business goals, and the influence of the internal and external context for data analytics. Akter et al. (2016) point out that interest in big data leads many companies to evolve the big data analytics capability and thus improve business performance.

On the other hand, big data analytics capability does not pay off for all companies. Moreover, very few organizations have been significantly impacted by implementing big data analytics capability. Additionally, Bygstad et al. (2019) describe that much of the information produced in hospitals is clinical and stored for documentation. Therefore, most of this documentation is never used. The potential of analytics resides in the reuse of this information for other purposes. There are several challenges involving technical, legal, and organizational aspects to achieve this. Furthermore, research shows that hospitals are not equipped to leverage the value of big data (Bygstad et al., 2019). "Analytics is a means, not an end in itself, but successful use of analytics for business and organizational purposes requires much more than a technology solution" (Bygstad et al., 2019). Therefore, big data analytics capability is expected to have no direct effect on patient service performance. This assumes that innovation ambidexterity fully mediates the effect on patient service performance. Therefore, a big data analytics capability does have no effect without the mediation of innovation ambidexterity. Against this background and with the data capabilities view in mind, hypothesis two is defined:

Hypothesis 2: A hospital department's big data analytics capability does not directly affect the patient service performance of a hospital department.

<u>Evidence-based decision-making cultures' effect</u>
Organizational culture plays an essential role in enabling an organization to create business value with analytics (Wang et al., 2019). It is defined as: "A set of collective values, beliefs, norms, and principles that guide organizations by defining appropriate behavior for various situations" (Ravasi & Schultz, 2006). According to Wang et al. (2019), many studies have shown that organizational culture is a significant obstacle to evidence-based decision-making e.g., (Kiron & Shockley, 2011; LaValle et al., 2011). Shifting the decision-making process from intuitive thinking and individual experience to 'the

facts' facilitated by big data analytics is a challenge organizations undertake (Wang et al., 2019). Davenport et al. (2010) describe an evidence-based decision-making culture as an aspect of organizational culture from a big data analytics perspective; a culture of embracing evidence-based management and embedding evidence-based decision-making in the core values and processes of the organization.

Researchers suggest that successful analytics use is most likely when an evidence-based decision-making culture is rooted in the enterprise's key business processes and that this kind of culture would tend to inspire an organization to measure, test, and evaluate quantitative evidence (Davenport, 2006; Kiron, Prentice, & Ferguson, 2012). Popovič, Hackney, Coelho, and Jaklič (2012) found that an organization with an analytical decision-making culture can positively affect the quality of the information provided by business intelligence systems. According to Ross, Beath, and Quaadgras (2013), building an evidence-based decision-making culture in an organization should ensure that all decision-makers share performance metrics that originate from one undisputed source. This provides decision-makers at all levels with near real-time feedback, articulates business rules and updates them with new facts when necessary, and regularly provides high-quality coaching to decision-makers. An evidence-based decision-making culture would allow healthcare organizations to make better use of real-time data, make more accurate diagnoses and better treatment decisions, and offer more reliable care to patients (Wang et al., 2019). Therefore, the following hypothesis is defined:

Hypothesis 3: An evidence-based decision-making culture positively affects the relationship between the data analytics capability of a hospital department to achieve innovation ambidexterity.

<u>Innovation ambidexterity and patient service performance of a hospital department</u>
The existing literature has recognized the added organizational value of business intelligence and analytics. However, literature offers a limited view of the impact of balancing innovative activities and ensuring performance goals (Božič & Dimovski, 2019). Although, finding new external knowledge from a narrow range of external sources (exploitative innovation) and finding new external knowledge from a broad range of external sources (explorative innovation) (J. J. P. Jansen et al., 2006). Acquiring new information and knowledge does not intrinsically lead to innovation and improved performance (Božič & Dimovski, 2019). Instead, firms must assimilate, transform and exploit this new knowledge to promote new or improved products and services (Chen, Chiang, & Storey, 2012). Innovation ambidexterity refers to finding a balance between exploitative and explorative innovation activities in the literature. Hospital departments are required to exploit current knowledge and explore new knowledge (Foglia et al., 2019). Against this background and with the data capabilities view in mind, the fourth hypothesis is defined:

Hypothesis 4: The higher the level of innovation ambidexterity in a hospital department, the higher the level of patient service performance.

2.4. Objective of the follow-up research

The follow-up research aims to test the effects of big data analytics capability, evidence-based decision-making culture, and innovation ambidexterity on patient service performance. It also fills the literature gaps related to driving factors of digital innovation and the mediating role of innovation ambidexterity on patient service performance.

This study examines a new conceptual framework using survey data of Dutch hospital departments and employing structural equation model (SEM) analysis from the partial least square (PLS) approach. In case the hypotheses are confirmed, this research proves that the ability of a hospital department to execute exploitation and exploration at the same time does influence the patient service performance. In addition, it will encourage hospitals to take the opportunity of emerging digital technologies by being committed to embracing new digital technologies and upgrading their innovation capabilities to enhance the quality of care.

3. Methodology

This chapter comprehensively describes and justifies the research design choices of the research performed.

3.1. Conceptual design: research method

The purpose of this study is to understand the relationships between big data analytics capability, evidence-based decision-making culture, innovation ambidexterity, and patient service performance of hospital departments. Which subsequently is tested with empirical data. This research has a deductive approach, whereas literature develops a theoretical framework for subsequent testing (Saunders et al., 2019). This is a new study since the combination of relationships has not been examined before. Data needs to be collected and analyzed to properly test the theoretical correlations between the abovementioned concepts (Saunders et al., 2019).

Saunders et al. (2019) mention that a deduction approach requires a highly structured methodology to facilitate replication to ensure reliability. Besides, analyzing and comparing the collected data is more convenient when data is structured. Saunders et al. (2019) designed the research onion containing several layers; philosophy, approach to theory development, methodological choice, strategy, time horizon, and techniques and procedures. This research is a cross-sectional study since it had a timeline of six months. In addition, the purpose of this study is achieved by collecting sufficient structured data; therefore, applying only one research method will be sufficient; mono method quantitative.

3.2. Technical design: elaboration of the method

To implement the conceptual design effectively, this section explains more about the technical design of this research.

3.2.1. Data Collection

the survey data was systematically collected through an online questionnaire that contained all the questions to test the research model and the relationships of the hypothesis. The target population consisted of team leads, managers, nurses, and doctors aligned with the research goals. They actively contact patients or have an insight into the patient service performance. Therefore, this group of respondents can provide valuable insights and are essential in answering the questions on research scope at the hospital department level. Foglia et al. (2019) mention that hospital wards represent the correct unit of analysis to investigate ambidexterity in the healthcare domain: "Wards have complex internal dynamics, requiring a high level of coordination among different professionals, who have to combine exploratory and exploitatory efforts daily." Besides, since ambidexterity is a comprehensive and complex process, studying it in an entire hospital would introduce too many confounding factors in the analysis. In addition, Gastaldi, Foglia, Lettieri, and Porazzi (2016) mentions four other reasons why hospital wards represent the best unit of analysis: specific internal dynamics, attitude to research and innovation activities, autonomy in the decision-making and resources allocation processes, and need of a high level of coordination among different professionals to be efficient. For the abovementioned reasons, this research focused on Dutch hospitals, divided into general hospitals, top clinical (teaching) hospitals, and academic medical hospitals.

For optimal reliability and validity results to test the research model, it is recommended to collect at least 90 completed surveys based on a statistical influence of 80% with two independent variables, a significance level of 5%, and a minimum R_2 value of 0.10 (Joseph F. Hair, 2017). The data will be conveniently and respondent-driven sampled from Dutch hospitals through the six Master students' professional networks within hospitals using email, telephone, and social networks. The anonymity of the respondents is guaranteed since the system did not track and personal information is not required to fill out the questionnaires. The selection of constructs was based on previous empirical and validated work to increase the internal validity and reliability of the questions. As this research was performed in a healthcare setting, some of the original items have to be reformulated to fit the context of Dutch healthcare.

To improve the content and validity of the survey items, this survey is pretested on several occasions by three medical practitioners. They have sufficient knowledge and experience of the survey subjects to provide valuable improvement suggestions.

3.2.2. Constructs and items

The survey comprises the topics mentioned in Chapter two: innovation ambidexterity, evidence-based decision-making culture, big data analytics capability, and patient service performance. Below is a description of each topic, the construction per topic, and the sources they were collected.

All indicators are based on prior scientific research and are measured using a 7-point Likert scale, ranging from 1: strongly disagree to 7: strongly agree. The entire survey is included in Appendix 1.

The construct big data analytics capability is measured using multiple reflective indicators. For this reason, the construct is more accurate in comparison to using a single item. Measures for big data analytics capability were adopted from Yu et al. (2020) and Wang, Kung, Wang, and Cegielski (2018).

Our department:

- … easily combines and integrates information from many data sources for use in our decision-making.
- … routinely uses data visualization techniques (e.g., dashboards to visualize the progression of a disease state) to support medical professionals (medical, medicine, and physician specialists) in understanding complex information.
- … makes dashboards and/or applications available on the (mobile) devices of our medical professionals (e.g., smartphones, computers).
- Our dashboards give us the ability to parse information to support root cause analysis (e.g., determine underlying pathology for symptoms).
- Our dashboards allow us to deploy information for continuous improvement of internal processes and/or quality of care services.

Evidence-based decision-making culture is considered a moderating construct on the relationship between big data analytics and innovation ambidexterity. Wang et al. (2019) devised three core items to measure an evidence-based decision-making culture.

Our department:

- ... typically uses insights based on facts to create new healthcare services.
- ... is open to new ideas and approaches that challenge current or future projects based on new insights.
- ... allows available information to be included in any decision-making process.

Innovation ambidexterity involves achieving a balance between explorative innovation and exploitative innovation. Measures for innovation ambidexterity are divided into exploratory innovation (Foglia et al., 2019; J. J. P. Jansen et al., 2006) and exploitative innovation (Foglia et al., 2018; Foglia et al., 2019; J. J. P. Jansen et al., 2006). Explorative and exploitative innovation are nonsubstitutable and interdependent. This means that the answers of both innovators need to be multiplied before analyzing the results of the innovation ambidexterity construct Gibson and Birkinshaw (2004).

<u>Explorative innovation</u>
Our department:

- ... invents new medical products and services.
- ... regularly experiments with new ideas.
- ... systematically acquires external knowledge (from other departments or hospitals, providers, and/or publications).
- ... quickly embraces new opportunities to serve our patients.
- ... quickly recognizes shifts and developments in healthcare.
- ... quickly analyzes and interprets changing market demands.

<u>Exploitative innovation</u>
Our department:

- ... regularly makes minor adjustments to our existing healthcare services and healthcare products.
- ... annually improves the efficiency of our internal processes and care services.
- ... expands care services for existing patients.
- ... introduces improved (already existing) care services and care products for our patients.
- Our medical professionals proceed efficiently in performing (outpatient) clinical activities and examinations.
- Professionals in our department have a clear understanding of duties and responsibilities.

Patient service performance can be considered as a higher-order formative construct. It contains three first-order measurement items: service attribute, patient relationship, and hospital image (Wu & Hu, 2012).

<u>Service attribute</u>
Our department:

- ... increases the availability of medical services using digital and/or data-driven innovations.
- ... increases the accessibility of medical services using digital and/or data-driven innovations.
- ... increases the quality of medical services using digital and/or data-driven innovations.

<u>Patient relationship</u>
Our department:

- ... increases patient satisfaction using digital and/or data-driven innovations.
- ... increases patient collaboration using digital and/or data-driven innovations.

- ... increases patient loyalty using digital and/or data-driven innovations.

Hospital image

Our department:

- ... enhances our hospital's reputation in the marketplace using digital and/or data-driven innovations.
- ... enhances our hospital's recognition in the marketplace using digital and/or data-driven innovations.
- ... enhances our hospital's position in the marketplace using digital and/or data-driven innovations.

3.3. Data analysis

The research model is examined using Partial Least Squares Equation Modeling (PLS-SEM) (Joseph F. Hair, 2017). It allows the estimation of complex cause-effect relationships in path models with latent variables (Joseph F. Hair, 2017). All analyses are performed with the software tool SmartPLS version 3.3.5. The PLS structural equation model comprises two elements: the structural model and the measurement model. The structural model (also called the inner model in PLS-SEM) represents the constructs. It also displays the relationships between the constructs. The measurement model (also referred to as the outer models in PLS-SEM) represents the relationships between the constructs and the indicator variables (Joseph F. Hair, 2017). In Paragraph 2.3, the theoretical framework of this research is developed. This framework is used as a starting point for designing the structural model, modeling the sequence of the constructs and the relationships between them (Joseph F. Hair, 2017). After the data cleaning, the quality of the measurement model will be determined with the following metrics:

Path model loadings

According to Joseph F. Hair (2017), a loading of 0.7 is considered close enough to 0,708 to be acceptable. Another rule is that loadings below 0.4 should permanently be deleted. Furthermore, loadings between 0.4 and 0.7 are exceptional to be removed when this increases the composite reliability above the suggested threshold level or are either preserved when it contributes to content validity (Joseph F. Hair, 2017).

Internal Consistency Reliability and Convergent Validity

The internal consistency reliability and convergent validity are measured using Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE). The Cronbach's Alpha evaluates the internal consistency reliability of the model (Joseph F. Hair, 2017, p. 111). This minimum score of 0.7 is also applicable for the Composite Reliability score, which also measures internal reliability. However, this measure of reliability takes the different outer loadings of the indicator variables into account (Joseph F. Hair, 2017, p. 111). The third measurement, the AVE score, evaluates the convergent validity and scores above 0.5 for all constructs.

Discriminant Validity

Discriminant validity is the extent to which a construct is genuinely distinct from other constructs by empirical standards (Joseph F. Hair, 2017, p. 115). According to Joseph F. Hair (2017), cross-loadings are the first approach to assess the discriminant validity of the indicators. All indicators outer loadings on the associated construct need to be greater than any of its cross-loadings on other constructs. The Fornell-Larcker is the second approach to assess discriminant validity. It compares the square root of the AVE values with the correlations of the latent variables (Joseph F. Hair, 2017, pp. 115-116). The highest correlation with any construct needs to be lower than the square root of the AVE values of each construct. The third and last approach of measuring the discriminant validity is the Heterotrait-Monotrait Ratio (HTMT). It estimates what the accurate correlation between two constructs would be if they were perfectly measured (Joseph F. Hair, 2017, p. 118). Joseph F. Hair (2017) suggests a threshold value of 0.90 if the path model includes conceptually very similar constructs. Therefore, the HTMT value above 0.90 suggests a lack of discriminant validity.

Structural model evaluation

According to Joseph F. Hair (2017, p. 192), the critical criteria for assessing the structural model in PLS-SEM are the significance of the path coefficients, the level of the R^2 values, the f^2 effect size, and the predictive relevance Q^2.

Three formative constructs form patient service performance. Therefore, the structural model is checked for collinearity, ensuring one construct does not increase the variance of the other. The VIF values should score lower than 5 (Joseph F. Hair, 2017, p. 194). Path coefficients show assumed relationships between the constructs and have values between 1 and -1. A path coefficient of 1 means a strong relationship between the constructs, and -1 means there is a negative relationship (Joseph F. Hair, 2017). The coefficient of determination is a measure for predicting the model's accuracy. It can score from 0 to 1, where 1 means the model is accurate (Joseph F. Hair, 2017). The effect size is used to evaluate whether the eliminated constructs significantly impact endogenous constructs. A value of 0.02 means minor effects, 0.15 value medium, and 0.35 significant effects (Joseph F. Hair, 2017). The Q^2 value is an indicator of predictive relevance where values greater than 0 indicate that predictive relevance is present between the constructs (Joseph F. Hair, 2017). To examine the predictive relevance of the structural model, the Q2 value is measured by the blindfolding calculation and cross-validates redundancy as recommended for the PLS-SEM method. If the Q2 value is higher than zero, the model can be considered as having predictive relevance (Joseph F. Hair, 2017).

3.4. Ethical aspects

This research follows a set of ethical principles derived from Saunders et al. (2019). There are no financial or other incentives for respondents to participate in this research. Respondents are informed in advance of the purpose of the study to ensure informed consent. Furthermore, participation in this research is voluntary. Respondents could provide their e-mail address if they would like to retrieve their answers or receive insights gained from the research. The e-mail address will only be used to inform the respondents about the research outcomes and is therefore not used to examine the data. The surveys are administered entirely anonymously, and therefore the results are not traceable to an individual or a hospital (Saunders et al., 2019).

4. Results

This section describes the survey implementation and the associated outcomes that have been obtained.

4.1. Data Examination

The survey data was collected in ten weeks, from September 2021 till December 2021. The minimum number of respondents required for a significance level of 5% and optimal R2 score according to Joseph F. Hair (2017, p. 26) is 90. Initially, a shorter period was planned to achieve a sufficient number of respondents (see Chapter 3). In the first period, there were too few respondents, which led to the decision to extend the survey (for up to ten weeks). In December 2021, the minimum amount of respondents was reached. In total, 334 people started the survey. Below, the data examination steps and results are briefly described.

- Missing data: The answers of this group were checked for a missing value with a maximum of 15 percent. Only the fully completed surveys met this criterion; 112 surveys.
- Screening questions: check whether the participants meet the criteria of the target group as described in Chapter 3. Five participants did not operate in the target group departments and did not meet the predefined criteria.
- Suspicious response patterns: since a 7-point scale is used to obtain answers, we checked for several suspicious response patterns as straight-lining, diagonal lining, and alternating extreme pole responses. A visual inspection of the responses was performed to identify any suspicious response patterns.
- Outliers: no outliers detected.

At the end of the data examination, 107 surveys were processed as input for the data analysis. This is sufficient, according to the criterium of Joseph F. Hair (2017).

4.2. Characteristics Data Population

To provide a better understanding of the results of the surveys, below the main characteristics of the data population are described. With 54.2%, the hospital type Collaborative Top Clinical Teaching Hospital is the most represented. Looking at the department's specialty, the answers are fairly spread out. Surgery with 14%, Orthopedics with 9.35%, and Anesthesiology with 8.41% form the top three specialties. In addition, we see that most departments focus primarily on insurable care 68.22%. The department's average number of employees (FTE) is 144, of which an average of 27.26 are medical doctors (FTE). The highest response rate to the department's existence in its current form of work is 25+ years at 29% and second at a rate of 22% 6-10 years. 38% of respondents answered that over 14,000 patients visit the department annually. The survey was completed mainly by doctors (specialists) 48.6%. The complete answers concerning the data population are attached in Appendix 3: Data Population.

4.3. Path Model Estimation

After collecting and cleaning the response data, the cleaned data file is uploaded to the SmartPLS tool. No errors or missing values were applied. The path model is estimated according to the conceptual model described in Chapter 2. The constructs Big Data Analytics Capability (BDAC) and Evidence-Based Decision-Making Culture (EBDMC) are both independent, whereas EBDMC is a moderating construct. Innovation Ambidexterity – Exploration (IA – Exploration) and Innovation Ambidexterity – Exploitation (IA – Exploitation) are mediating constructs. Patient Service Performance (PSP) is a dependent construct with three first-order components; Service Attribute, Patient Relationship, and Hospital Image.

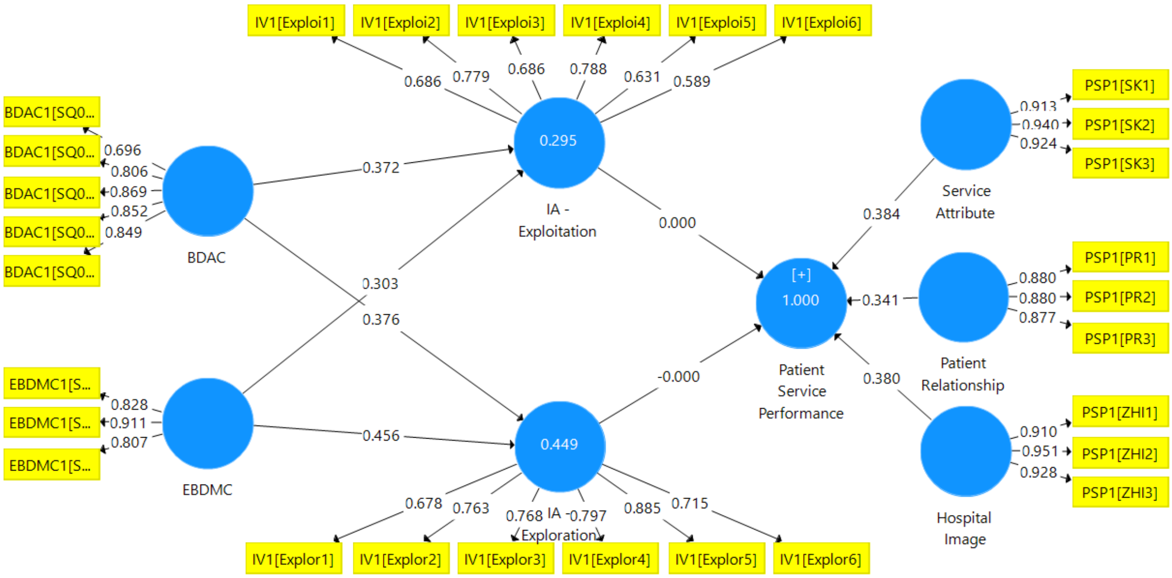

Figure 4: Initial Path Model Loadings

Most indicators have a loading of 0.7 or higher. The lowest indicator has a loading of 0.588, and the highest indicator has a loading of 0.916. A common rule of thumb is that the standardized outer loadings should be 0.708 or higher. According to Joseph F. Hair (2017), a loading of 0.7 is considered close enough to 0,708 to be acceptable. Another rule is that loadings below 0.4 should always be deleted. Furthermore, between 0.4 and 0.7 are exceptional to be removed when this increases the composite reliability above the suggested threshold level or are either preserved when it contributes to content validity (Joseph F. Hair, 2017). The path model loadings in figure 4 do not have a loading below 0.4. It does have loadings between 0.4 and 0.7: Exploi1 0.686, Exploi3 0.686, Exploi5 0.631, Exploi6 0.588, BDAC1 0.696, and Explor1 0.678. Exploi5 and Exploi6 are the indicators that score the lowest. After deleting both indicators, the construct IA – Exploitation fully loads between 0.4 and 0.7 (see figure 5).

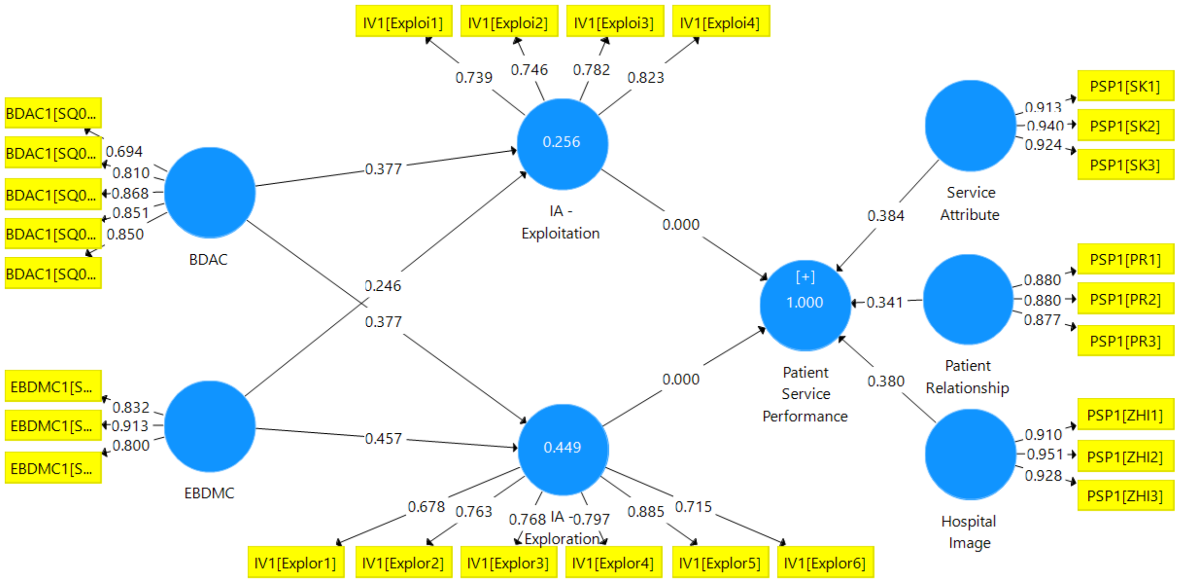

Figure 5: Final Path Model Loadings

4.4. Internal Consistency Reliability and Convergent Validity

The internal consistency reliability and convergent validity are measured using Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE) (table 6). The Cronbach's Alpha evaluates the internal consistency reliability of the model (Joseph F. Hair, 2017, p. 111). All constructs score above 0.7 with the Cronbach's Alpha. This minimum score of 0.7 is also applicable for the Composite Reliability score, which also measures the internal reliability. However, this measure of reliability takes the different outer loadings of the indicator variables into account (Joseph F. Hair, 2017, p. 111). The third measurement, the AVE score, evaluates the convergent validity and scores above 0.5 for all constructs. The outcome of the scores is true to expectation since all loadings of the path model were above or near 0.7. Concluding, the reliability and convergent validity measures are positive and therefore the model can be regarded as reliable and valid.

	Cronbach's Alpha	**Composite Reliability**	**AVE**
BDAC	0.874	0.909	0.667
EBDMC	0.807	0.886	0.722
Hospital Image	0.922	0.951	0.865
IA - Exploitation	0.777	0.856	0.598
IA - Exploration	0.861	0.897	0.594
Patient Relationship	0.853	0.911	0.772
Service Attribute	0.916	0.947	0.857

Table 6: Construct Reliability and Validity

4.5. Discriminant Validity

Discriminant validity is the extent to which a construct is genuinely distinct from other constructs by empirical standards (Joseph F. Hair, 2017, p. 115). According to Joseph F. Hair (2017), cross-loadings are the first approach to assess the discriminant validity of the indicators. The cross-loadings are shown in table 7. All indicators outer loadings on the associated construct are more significant than any of its cross-loadings on other constructs (table 8).

	BDAC	EBDMC	IA - Exploitation	IA - Exploration	Patient Relationship	Service Attribute	Hospital Image
BDAC1[SQ001]	**0.694**	0.352	0.304	0.436	0.178	0.303	0.319
BDAC1[SQ002]	**0.81**	0.262	0.279	0.372	0.239	0.294	0.39
BDAC1[SQ003]	**0.868**	0.181	0.359	0.371	0.296	0.321	0.364
BDAC1[SQ004]	**0.851**	0.226	0.487	0.465	0.43	0.397	0.528
BDAC1[SQ005]	**0.85**	0.149	0.354	0.406	0.39	0.386	0.421
EBDMC1[SQ001]	0.15	**0.832**	0.306	0.403	0.211	0.282	0.201
EBDMC1[SQ002]	0.243	**0.913**	0.372	0.548	0.31	0.276	0.207
EBDMC1[SQ003]	0.337	**0.8**	0.208	0.474	0.227	0.186	0.146
IV1[Exploi1]	0.164	0.282	**0.739**	0.556	0.335	0.407	0.349
IV1[Exploi2]	0.499	0.319	**0.746**	0.594	0.376	0.496	0.363
IV1[Exploi3]	0.304	0.2	**0.782**	0.535	0.487	0.456	0.497
IV1[Exploi4]	0.356	0.29	**0.823**	0.666	0.312	0.439	0.311
IV1[Explor1]	0.313	0.324	0.502	**0.678**	0.419	0.452	0.381
IV1[Explor2]	0.397	0.439	0.526	**0.763**	0.388	0.531	0.289
IV1[Explor3]	0.446	0.514	0.51	**0.768**	0.459	0.501	0.386
IV1[Explor4]	0.333	0.468	0.664	**0.797**	0.41	0.465	0.43
IV1[Explor5]	0.481	0.504	0.662	**0.885**	0.463	0.49	0.421
IV1[Explor6]	0.348	0.323	0.665	**0.715**	0.407	0.38	0.45
PSP1[PR1]	0.367	0.32	0.468	0.491	**0.88**	0.802	0.643
PSP1[PR2]	0.319	0.181	0.423	0.48	**0.88**	0.605	0.58
PSP1[PR3]	0.327	0.278	0.408	0.482	**0.877**	0.579	0.648
PSP1[SK1]	0.332	0.285	0.558	0.578	0.649	**0.913**	0.616
PSP1[SK2]	0.391	0.2	0.5	0.547	0.735	**0.94**	0.672
PSP1[SK3]	0.446	0.33	0.575	0.574	0.721	**0.924**	0.692
PSP1[ZHI1]	0.427	0.288	0.503	0.514	0.654	0.703	**0.91**
PSP1[ZHI2]	0.466	0.181	0.448	0.484	0.711	0.663	**0.951**
PSP1[ZHI3]	0.515	0.139	0.432	0.418	0.615	0.623	**0.928**

Table 7: Discriminant Validity – Cross Loadings

The Fornell-Larcker is the second approach to assess discriminant validity. It compares the square root of the AVE values with the correlations of the latent variables (Joseph F. Hair, 2017, pp. 115-116). Table 8 shows that the highest correlation with any construct is lower than the square root of the AVE values of each construct.

	BDAC	EBDMC	Hospital Image	IA - Exploitation	IA - Exploration	Patient Relationship	Service Attribute
BDAC	**0.817**						
EBDMC	0.285	**0.85**					
Hospital Image	0.504	0.219	**0.93**				
IA - Exploitation	0.447	0.354	0.496	**0.773**			
IA - Exploration	0.507	0.564	0.508	0.761	**0.77**		
Patient Relationship	0.386	0.298	0.711	0.494	0.552	**0.879**	
Service Attribute	0.422	0.293	0.713	0.587	0.611	0.759	**0.926**

Table 8: Discriminant Validity – Fornell Larcker Criterion

The third and last approach of measuring the discriminant validity is the Heterotrait-Monotrait Ratio (HTMT). It would estimate the actual correlation between two constructs if they were perfectly measured (Joseph F. Hair, 2017, p. 118). As shown in table 9, the highest correlation is between IA - Exploitation and IA - Exploration with a correlation of 0.934. After the first HTMT check in SmartPLS, a second bootstrapping check with 5000 samples is performed. The average of this check is 0.934. However, the percentage of 97,5 shows a value of 1.009. Since the construct innovation ambidexterity, which is a combination of the two opposing modes IA - Exploration and IA - Exploitation, the correlation of 0.934 is sufficient.

	BDAC	EBDMC	Hospital Image	IA - Exploitation	IA - Exploration	Patient Relationship	Service Attribute
BDAC							
EBDMC	0.342						
Hospital Image	0.553	0.251					
IA - Exploitation	0.507	0.437	0.58				
IA - Exploration	0.575	0.663	0.573	0.934			
Patient Relationship	0.434	0.35	0.799	0.597	0.644		
Service Attribute	0.465	0.34	0.775	0.689	0.689	0.85	

Table 9: Discriminant Validity – Heterotrait-Monotrait Ratio (HTMT)

4.6. Structural Model Evaluation

In the previous paragraphs, the reliability and validity of the data are confirmed. This paragraph continues the analysis. According to Joseph F. Hair (2017, p. 192), the critical criteria for assessing the structural model in PLS-SEM are the significance of the path coefficients, the level of the R^2 values, the f^2 effect size, and the predictive relevance Q^2.

4.6.1. Collinearity Assessment

Three formative constructs form patient service performance. Therefore, the structural model needs to be checked for collinearity, ensuring one construct does not increase the variance of the other. In the table below (table 10), the VIF values are shown, which should score lower than 5 (Joseph F. Hair, 2017, p. 194). The VIF values of the constructs are between 1.094 and 1.407. This means that there are no critical scores of collinearity present.

	IA	**PSP**
BDAC	1.213	1.407
EBDMC	1.094	
IA		1.407
Moderating Effect 1	1.118	

Table 10: Collinearity Assessment – Inner VIF Values

4.6.2. Path Coefficients

Path coefficients show assumed relationships between the constructs and have values between 1 and -1. A path coefficient of 1 means a strong relationship between the constructs, and -1 means there is a negative relationship (Joseph F. Hair, 2017). The results (table 11) show that the moderating effect has the lowest score of 0.1. The score of 0.1 is very close to 0, which means there is no relationship. The relationship between BDAC and PSP is also relatively low. The highest score is from IA, with PSP of 0.548.

	IA	**PSP**
BDAC	0.399	0.192
EBDMC	0.391	
IA		0.548
Moderating Effect 1	0.1	

Table 11: Path Coefficients

4.6.3. Coefficient of Determination (R^2 value)

The coefficient of determination is a measure for predicting the model's accuracy. It can score from 0 to 1, where 1 means the model is accurate (Joseph F. Hair, 2017). All R^2 values are between 0.4 and 0.5 (table 12), which is approximately in the middle of accuracy.

	R Square	R Square Adjusted
IA	0.432	0.415
PSP	0.451	0.44

Table 12: R^2 value

4.6.4. Effect Size f^2

The effect size is used to evaluate whether the eliminated constructs significantly impact endogenous constructs. A value of 0.02 means minor effects, 0.15 value medium, and 0.35 significant effects (Joseph F. Hair, 2017). Table 13 shows the results of the Effect Size f^2. The moderating effect scores the lowest (no effect), whereas IA and PSP score the highest with a score of 0.389 (significant effects).

	IA	PSP
BDAC	0.23	0.048
EBDMC	0.246	
IA		0.389
Moderating Effect 1	0.014	

Table 13: Effect Size f2

4.6.5. Predictive Relevance Q^2

The Q^2 value is an indicator of predictive relevance where values greater than 0 indicate that some sort of predictive relevance is present between the constructs (Joseph F. Hair, 2017). Table 14 shows that only the variables IA and PSP have an indicator of predictive relevance.

	Q^2 value
IA	0.401
PSP	0.433

Table 14: Predictive Relevance Q2

4.7. Hypotheses Testing

This paragraph focuses on the cause-effect relationships that represent the underlying structural theories of the path model. Before the theory and hypotheses from Chapter 2 can be examined, the constructs regarding innovation ambidexterity need to be merged. Therefore, all indicators of IA - Exploitation IV1[Exploi1] till IV1[Exploi4] and IA - Exploration IV1[Explor1] till IV1[Explor6] are multiplied. The multiplication of the two indicators led to 24 indicators representing the construct innovation ambidexterity (figure 6). Furthermore, since EBDMC is considered a moderating variable, Moderating Effect 1 is added. In contrast, innovation ambidexterity is identified as the dependent variable, BDAC is the independent variable, and EBDMC is identified as a moderator variable (figure 6).

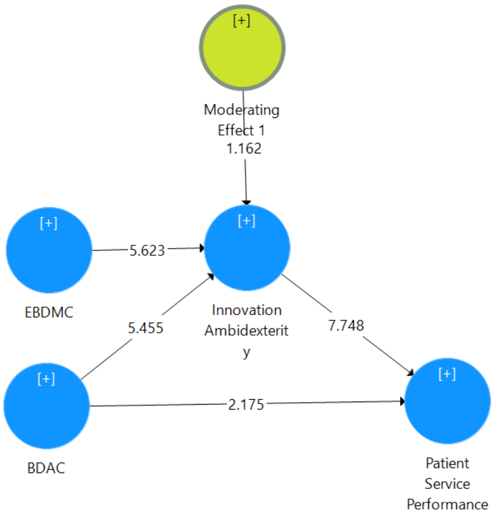

Figure 6: Structural Path Model Loadings

To test the hypotheses, bootstrapping with 5000 samples and a significance level of 5% was performed. At a significance level of 5%, t-values should be higher than 1.96 and p-values lower than 0.1 (Joseph F. Hair, 2017). In table 16, the Path Coefficient is measured as well. This calculates the standardized coefficients approximately between -1 and +1 for every relationship in the model. Path coefficients close to +1 indicate a robust positive relationship and vice versa for negative values (Joseph F. Hair, 2017, p. 90). The analysis result is shown in the table below (table 15).

	Path Coefficient	Standard Deviation	T Statistics	P Values
BDAC -> Innovation Ambidexterity	0.399	0.073	5.455	0
BDAC -> Patient Service Performance	0.192	0.088	2.175	0.03
EBDMC -> Innovation Ambidexterity	0.391	0.069	5.623	0
Innovation Ambidexterity -> Patient Service Performance	0.548	0.071	7.748	0
Moderating Effect 1 -> Innovation Ambidexterity	0.1	0.086	1.162	0.245
BDAC -> Innovation Ambidexterity -> Patient Service Performance	0.219	0.05	4.358	0
EBDMC -> Innovation Ambidexterity -> Patient Service Performance	0.214	0.053	4.02	0
Moderating Effect 1 -> Innovation Ambidexterity -> Patient Service Performance	0.055	0.048	1.138	0.255

Table 15: Bootstrapping Structural Path Model Loadings

When looking at the results in table 15, most of the values meet the set of criteria. This shows that the construct of big data analytics capability has a significant effect on innovation ambidexterity (T= 5.455 and P= 0) and patient service performance (T=2.175 and P=0.03). However, the big data analytics capability score on innovation ambidexterity (path coefficient= 0.399) is somewhat higher than the score on patient service performance (path coefficient= 0.192). This allows us to conclude that both constructs load significantly. However, the significance level on innovation ambidexterity is higher.

The scores on the construct patient service performance are also both significant. The construct big data analytics capability has a T-value of 2.175 and P-value of 0.03, and the construct innovation ambidexterity has a T-value of 7.747 and a P-value of 0. When comparing the Path Coefficient scores of both constructs, the construct Innovation Ambidexterity scores the highest with a score of 0.548 (difference of 0.356).

The moderating effect is the only score that does not meet the criteria. With a T-value of 1.162, the score is lower than the threshold of 1.96. The P-value of 0.245 scores too high since the scores need to be lower than 0.1. The Path Coefficient score of 0.1 confirms this. Therefore, we can conclude that there is no relationship between big data analytics capability and innovation ambidexterity constructs with a moderating effect of evidence-based decision-making culture. Although there is no moderating relationship, we observe that there is, however, a direct effect of evidence-based decision-making culture on innovation ambidexterity (Path Coefficient= 0.391, T-value= 5.623, and P-value= 0).

Lastly, the loadings of the indirect effects are shown (bottom three lines of table 15). The combination of BDAC, IA, and PSP is significant (T-value= 4.358 and P-value= 0). In addition, the combination of EBDMC, IA, and PSP is significant as well (T-value= 4.02 and P-value= 0). The Coefficient of the first-mentioned combination is 0.219. The Coefficient of the second-mentioned combination is 0.214. Comparing the loadings of both indirect effects, we can conclude that BDAC, IA, and PSP are the strongest combination (a small Coefficient difference of 0.005). Below a comparison of the data results with the pre-established theoretical hypotheses is made.

H1: A hospital department's big data analytics capability positively affects innovation ambidexterity.
This hypothesis is correct. Big data analytics capability is an independent variable with the highest score on innovation ambidexterity.

H2: A hospital department's big data analytics capability does not directly affect the patient service performance of a hospital department.
This hypothesis is partly correct. Big data analytics capability does have a direct effect on patient service performance. However, this effect scores low. Therefore, we can conclude that big data analytics capability has a low direct impact on patient service performance.

H3: An evidence-based decision-making culture positively affects the relationship between the data analytics capability of a hospital department to achieve innovation ambidexterity.
Based on the results in table 16, hypothesis 3 is declined as there is no significant effect of the moderating variable.

H4: The higher the level of innovation ambidexterity in a hospital department, the higher the level of service performance.

Innovation ambidexterity does have a significant effect on patient service performance. This is the highest significance effect of all constructs. Therefore, we can conclude that hypothesis 4 is correct.

4.8. Multi-group analysis

In the previous paragraphs, we concluded that EBDMC does not moderate the relationship between BDAC and IA. With the multi-group analysis, we would like to examine if the result improves once the group of EBDMC is split into two groups. The average response of EBDMC is 5.32. Therefore, we chose to classify the construct into the following two groups. If EBDMC is equal to or greater than the mean of 5.32, then category two is assigned. If EBDMC is less than 5.32, then category one is assigned. Classifying the categories based on the mean has the advantage that the distribution of the groups is approximately equal, and a multi-group analysis can be performed. For the group with a higher score on EBDMC, we expect the correlation to be higher than the group with a lower score. For this analysis, the Multi-Group Analysis in SmartPLS is used. In the table below, the results are shown (table 16).

	p-Value Category 1	**p-Value Category 2**
BDAC -> Innovation Ambidexterity	0.104	0
BDAC -> Patient Service Performance	0.322	0.007
Innovation Ambidexterity -> Patient Service Performance	0	0

Table 16: Multi-group analysis EBDMC categories

The results of the multi-group analysis show there is a difference between both categories. Category two scores higher compared to category one on BDAC -> Innovation Ambidexterity. This means that category two significantly affects the relation between the two variables. Furthermore, both categories score significant on Innovation Ambidexterity -> Patient Service Performance.

5. Discussion, conclusions, and recommendations

Over the past few years, the confluence of several trends in the health industry has accelerated. To ensure that hospitals can continue to operate while enhancing the quality of care, hospitals can use new innovative information technologies. Research results of Gilbert (2018) and Taylor (2020) reveal that healthcare providers have high ambitions for digital optimization and transformation. However, their ambitions are hindered by a significant gap in their innovation ambidexterity capabilities to execute and their frequently overlapping optimization and transformation efforts.

Literature research and a survey were administered to offer insights into how hospitals might innovate care delivery by using dynamic capabilities such as big data analytics capability and evidence-based decision-making culture. This chapter contains a discussion of the outcomes with corresponding conclusions, recommendations for practice, and an explanation of the study's limitations translated into recommendations for further research.

5.1. Discussion and Conclusions

Big data analytics enables various analytical techniques (e.g., statistical methods and optimization) to process large amounts of health data in various forms (e.g., text-based health documents, physician's written notes and prescriptions, and medical imaging) for harvesting business insights (Wang et al., 2019). Literature asserts that a big data analytics capability facilitates developing innovation ambidexterity (Van de Wetering, 2021a, Van de Wetering et al., 2021d; Yu et al., 2020). This research examined the particular role of the big data analytics capability in applying innovation ambidexterity as a mediator to the patient service performance of a hospital department. One of the findings confirms the assertion of previous research and shows that a big data analytics capability of a hospital department positively affects innovation ambidexterity. This means that big data analytics capability is crucial in achieving innovation ambidexterity.

An evidence-based decision-making culture allows healthcare organizations to use real-time data better, make more accurate diagnoses and treatment decisions, and offer more reliable care to patients (Wang et al., 2019). We examined the effect of evidence-based decision-making culture on the relationship between the data analytics capability of a hospital department to achieve innovation ambidexterity. Empirical research has proven that an evidence-based decision-making culture does not affect the relationship between the data analytics capability to achieve innovation ambidexterity. With this information in hand, we can conclude that evidence-based decision-making culture has no moderating influence on big data analytics capability and the level of innovation ambidexterity.

On the other hand, empirical research shows a direct effect of evidence-based decision-making culture on innovation ambidexterity. Literature has proven the positive effect of a digital dynamic capability on a higher-order dynamic organizational capability. However, evidence-based decision-making culture has no digital dynamic capability and still positively affects innovation ambidexterity. The existing literature with studies on evidence-based decision-making culture indicates the importance of the organizational culture in enabling an organization to create business value with analytics (Wang et al., 2019). The empirical results of both big data analytics and evidence-based decision-making culture show that both variables score roughly the same. Big data analytics capability has the highest score on innovation ambidexterity of the two. Based on the confirmation of the empirical study, we can assume that evidence-based decision-making culture is as much a driver of innovation ambidexterity as big data analytics capability.

Another interesting analysis is the direct effect of big data analytics capability on patient service performance. Since there was no existing literature about this effect and to confirm the results of existing literature about the mediating role of innovation ambidexterity, this research examined the direct effect of a big data analytics capability on patient service performance. Concluding, the big data analytics capability of a hospital department does have a minimal impact on the service performance of the department. However, it is more important to appoint that the big data analytics capability with a mediating effect of innovation ambidexterity is more powerful and has more effect on the department's performance than big data analytics capability itself. With the assertions mentioned above, we can conclude that innovation ambidexterity has a full mediating effect on patient service performance, which is also confirmed in multiple scientific studies. The higher the level of innovation ambidexterity in a hospital department, the higher the level of service performance.

After the analysis of the hypotheses testing was completed, a multi-group analysis on the construct EBDMC was performed. Previous results showed that EBDMC did not affect the relationship between BDAC and IA. However, the results of the multi-group analysis showed there is indeed an effect between BDAC and IA on EBDMC category two. This means that the category with a survey score higher than 5.32 does have a significant effect. Consequently, when a hospital department facilitates an evidence-based decision-making culture, it also positively affects the relationship between big data analytics capability and innovation ambidexterity of the department.

5.2. Recommendations for Practice

The previous paragraph discussed the theoretical research results in comparison with the retrieved survey data. This paragraph is focused on the recommendations for practice.

'Innovation is key' is a commonly discussed term that is often said when comparing current performance and desired performance goals. In this digital age and with the current situation, innovation is often a means to increase the performance quality of care. This research has confirmed that innovation in the form of innovation ambidexterity has a significant role in increasing patient service performance. In addition, we have also seen that other factors support innovation ambidexterity. This research has confirmed that both big data analytics and evidence-based decision-making culture positively affect innovation ambidexterity and, therefore, patient service performance. This means, when investing in big data analytics capability, a hospital department can enable various analytical techniques (e.g., statistical methods and optimization) to process health data into business insights. Subsequently, the insights generated can be displayed on healthcare performance dashboards, which support the daily tasks of healthcare delivery (such as doctors and nurses), enabling them to make smarter and faster data-driven decisions.

5.3. Limitations and Recommendations for Further Research

The limitations of this study are described below:

- Since this study took place during a pandemic, the results may be different if the study had taken place at a different period.
- Since the survey was web-based, several recipients ignored the request to complete the questionnaire.
- The length of the questionnaire presented a limitation, and a lack of interest was observed in several respondents who participated in the research. This resulted in several incomplete surveys.

After completing the research and given its limitations, the following recommendations can be made for future research:

- The research has shown that big data analytics capability and evidence-based decision-making culture enhance the degree of innovation ambidexterity. There has been no research into the direct relationship between big data analytics capability and evidence-based decision-making culture. Future research can examine the relationship between both variables.
- Innovation ambidexterity has a significant influence on the quality of care. In this research, the influence of two independent variables is examined. Literature asserts that innovation ambidexterity is affected by more variables. Future research can examine the other relationships and significance levels with innovation ambidexterity.
- This research is based on Dutch hospital departments. In further research, it can be performed for other countries as well. There might be a difference to be discovered between the hospital departments of other countries. For example, future research can focus on European or non-western hospitals.

5.4. Acknowledgments

I would like to thank all the hospital professionals involved in this research for their valuable contribution by filling in the questionnaire and providing relevant insights on innovation ambidexterity in hospital wards. Additionally, I would like to thank my primary supervisor, who guided me throughout this research. Last but not least, I would like to express my gratitude to my co-students for the collaboration.

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Appendix 1: Invitation and Follow-up Messages Acquiring Respondents (in Dutch)

First message on LinkedIn:

Beste [first name],

Voor mijn afstudeeronderzoek van de Master Business Process Management and IT onderzoek ik digitalisering binnen ziekenhuizen. Ik wil u vragen of u 15 min van uw kostbare tijd wil vrijmaken om deel te nemen aan een survey: https://lnkd.in/grvb94_i

Mvg, Chanel Meulenkamp

Second message on LinkedIn (after accepting connection request):

Beste [first name],

Dank voor het accepteren van mijn uitnodiging!
Als masterstudent werk ik aan een uitvoerig onderzoek naar de digitale transformatie binnen ziekenhuizen.

Ik ben op zoek naar afdelingshoofden (management), artsen, verpleegkundig specialisten en andere zorgspecialisten die 15 minuten van hun kostbare tijd willen vrijmaken om (anoniem) een vragenlijst over digitalisering binnen ziekenhuizen in te vullen. Link naar de vragenlijst: https://lnkd.in/grvb94_i

Deelname aan dit onderzoek is van groot belang! De stijgende vraag naar zorgdiensten vereist een dynamische ziekenhuisomgeving die momenteel gebukt gaat onder uitputtende management-, regelgeving- en administratieve processen. Nieuwe digitale informatietechnologieën bieden ziekenhuizen diverse mogelijkheden om te innoveren en zo deze uitdagingen het hoofd te bieden.

Het delen van dit bericht binnen uw netwerk/ziekenhuisorganisatie wordt zeer gewaardeerd en komt uiteindelijk ten goede aan alle zorgprofessionals!

Mocht u vragen hebben, laat het gerust weten.
Alvast hartelijk dank voor uw medewerking.

Met vriendelijke groet,

Chanel Meulenkamp
(Student Business Process Management and IT)
E-mail: chanel_meulenkamp@hotmail.com
Mobiel: +316 10 43 03 02

Appendix 2: Definitive Survey in Limesurvey (in Dutch)

Digitale transformatie binnen ziekenhuisafdelingen

De impact van Big Data Analytics en Lightweight IT op innovatief vermogen en kwaliteit van zorg.

Introductie

Welkom bij deze enquête over digitale transformatie binnen Nederlandse ziekenhuisafdelingen. Deze enquête is onderdeel van een lopend onderzoek van de Open Universiteit. Het onderzoek wordt uitgevoerd door een samenwerking van afstuderende studenten van de Master Business Process Management & IT aan de Open Universiteit, onder begeleiding van hoofdonderzoeker dr. Rogier van de Wetering, Associate Professor in Information Systems and Business Processes (rogier.vandewetering@ou.nl).

Structuur van de enquête

Deze enquête is als volgt gestructureerd: na enkele achtergrondvragen volgen vragen over Patient Service Performance en Operationele Performance. Dit onderdeel wordt gevolgd door vragen over Innovatief Vermogen, Patient Agility en Evidence Based Decision Making Culture. De enquête wordt afgesloten met vragen over de inzet van Lightweight IT, Big Data Analytics Capability en Artificial Intelligence-toepassingen.

Het invullen van deze enquête zal ongeveer 15 minuten duren.

Bij voorbaat hartelijk dank voor uw tijd om deel te nemen aan dit onderzoek.

Er zijn 19 vragen in deze enquête.

Geef hier uw e-mailadres op om de bevindingen en aanbevelingen van dit onderzoek te ontvangen (optioneel). U kunt op elk moment gedurende het onderzoek uw deelname aan deze studie intrekken, mits u uw mailadres heeft opgegeven.

Vul uw antwoord hier in:

Geef het type ziekenhuis aan waar u werkzaam bent:

- Universitair Medisch Centrum (UMC)
- Samenwerkend Topklinisch opleidingsziekenhuis (STZ)
- Samenwerkend Algemeen Ziekenhuis (SAZ)
- Overig Algemeen Ziekenhuis (OAZ)
- Overige

Geef het specialisme van uw afdeling aan:

- Anesthesiologie
- Apotheek
- Cardiologie
- Cardiothoracale Chirurgie
- Chirurgie
- Dermatologie
- Endocrinologie
- Geriatrie
- Hematologie
- Immunologie

- Infectieziekten
- Intensive Care Volwassenen
- Intensive Care Kinderen
- Inwendige Geneeskunde
- Keel-, neus- en oorziekten
- Kindergeneeskunde
- Neonatologie
- Longziekten
- Maag-, darm en leverziekten
- Medische psychologie
- Mondziekten-kaakchirurgie/Ziekenhuistandheelkunde
- Neurochirurgie
- Neurologie
- Nierziekten
- Oncologie
- Oogheelkunde
- Orthopedie
- Plastische en Reconstructieve chirurgie
- Psychiatrie
- Reumatologie
- Revalidatie
- Spoedeisende hulp
- Sportgeneeskunde
- Urologie
- Vasculaire geneeskunde
- Verloskunde/Gynaecologie
- Overige

Onze afdeling richt zich primair op:

- Verzekerbare zorg
- Niet-verzekerbare zorg
- Allebei (ongeveer evenveel)

Hoeveel artsen (fte) zijn werkzaam binnen uw afdeling (met arts wordt bedoeld medewerker met minimaal kwalificatie basisarts):

In dit veld mogen alleen cijfers ingevoerd worden.
Vul uw antwoord hier in:

Hoeveel medewerkers (fte) zijn in totaal werkzaam binnen uw afdeling (inclusief ondersteunend en administratief):

In dit veld mogen alleen cijfers ingevoerd worden.
Vul uw antwoord hier in:

Geef aan hoelang uw afdeling bestaat in haar huidige vorm gezien vanuit de werkprocessen:

- 0-5 jaar
- 6-10 jaar
- 11-15 jaar
- 16-20 jaar
- 21-25 jaar
- 25+ jaar

Geef een benadering van het aantal patiënten aan dat uw afdeling jaarlijks bezoekt (Dit zijn zowel nieuwe patiënten als herhaalbezoeken):

- < 4.000
- 4.000 – 6.500
- 6.501 – 9.000
- 9.001 – 11.500
- 11.501 – 14.000
- > 14000

Geef uw huidige functie binnen de organisatie aan:

- Afdelingshoofd
- Teamleider
- Manager bedrijfsvoering
- Verpleegkundig specialist
- Physician assistant
- Chef de Clinique
- Arts (Specialist)
- AIOS
- ANIOS
- Overige

Geef aan hoeveel jaar u op uw huidige afdeling werkt:

- 0–5 jaar
- 6–10 jaar
- 11–15 jaar
- 16–20 jaar
- 21–25 jaar
- 25+ jaar

Hoeveel jaar werkervaring heeft u na het afronden van uw opleiding als basisarts? (Indien u geen arts bent, kunt u in n.v.t. invullen)

- 0–5 jaar
- 6–10 jaar
- 11–15 jaar
- 16–20 jaar
- 21–25 jaar
- 25+ jaar
- n.v.t.

Big Data Analytics Capability

Big Data Analytics Capability (BDAC) betreft het vermogen van ziekenhuizen om grote volumes (medische) gegevens in verschillende vormen (bijvoorbeeld sensordata, labtesten, DNA-gegevens) te verwerven, verwerken, op te slaan en te analyseren.

BDAC betreft eveneens het vermogen om deze analyses om te zetten naar inzichten, besluiten en acties die waarde toevoegen, prestaties meten en tot competitief voordeel leiden. Het gaat hierbij bijvoorbeeld om het analyseren van bloedwaardes, opgeslagen in één database, waarmee trends kunnen worden ontdekt in en/of voorspellingen kunnen worden gedaan over de ontwikkeling van de gezondheid of het ziektebeeld van een patiënt.

Onze afdeling:
Kies het toepasselijke antwoord voor elk onderdeel:
helemaal oneens – oneens - enigszins oneens – neutraal - enigszins eens – eens - helemaal mee eens

- … combineert en integreert gemakkelijk informatie uit vele gegevensbronnen voor gebruik bij onze besluitvorming rondom zorgdienstverlening.
- … gebruikt routinematig datavisualisatietechnieken (bijv. dashboards ter visualisatie van de ontwikkeling van een ziektebeeld) om medische professionals (medisch-, geneeskundig- en arts-specialisten) te ondersteunen bij het begrijpen van complexe informatie.
- … stelt dashboards en/of applicaties beschikbaar op de (mobile) devices van onze medische professionals (bijv. smartphones, computers).
- Onze dashboards geven ons de mogelijkheid om informatie te ontleden voor het ondersteunen van root cause analyses (bijv. vaststellen onderliggend ziektebeeld bij symptomen).
- Onze dashboards geven ons de mogelijkheid om informatie in te zetten voor continue verbetering van interne processen en/of kwaliteit van zorgdienstverlening.

Evidence Based Decision Making Culture
Evidence Based Decision Making Culture betreft de (bedrijfs)cultuur waarin op feiten gebaseerd management wordt omarmd en op feiten gebaseerde besluitvorming wordt verankerd in de kernwaarden en processen van de afdeling.

Bij ziekenhuizen speelt de afdelingscultuur een belangrijke rol bij het in staat stellen van een afdeling om op basis van feiten bedrijfswaarde te creëren. Een besluitvormingscultuur betreft een cultuur waarin op feiten gebaseerd management wordt omarmd en op feiten gebaseerde besluitvorming wordt verankerd in de kernwaarden en processen van de afdeling.

Onze afdeling:

- … gebruikt meestal inzichten gebaseerd op feiten voor het creëren van nieuwe zorgdiensten.
- … staat open voor nieuwe ideeën en benaderingen die huidige of toekomstige projecten uitdagen op basis van nieuwe inzichten.
- … maakt het mogelijk om beschikbare informatie op te nemen in elk besluitvormingsproces.

Innovatief vermogen
Het innovatief vermogen van een ziekenhuisafdeling betreft het kunnen omzetten van nieuwe mogelijkheden in nieuwe en/of verbeterde zorgproducten en -diensten.

Binnen de uitvoering van innovatieactiviteiten wordt continu gezocht naar een balans tussen ‘exploreren’ en ‘exploiteren’. Hiermee worden respectievelijk radicale innovaties geïntroduceerd (identificeren en invoeren van nieuwe mogelijkheden), danwel incrementele innovaties doorgevoerd (doorontwikkelen van bestaande mogelijkheden). Een juiste balans is cruciaal in het managen van de trade-off tussen de borging van hoge kwaliteit van zorglevering en kostenbeheersing.

Onze afdeling:
Kies het toepasselijke antwoord voor elk onderdeel:
helemaal oneens – oneens - enigszins oneens – neutraal - enigszins eens – eens - helemaal mee eens

- … bedenkt nieuwe medische producten en diensten.
- … experimenteert regelmatig met nieuwe ideeën.
- … verwerft op systematische wijze externe kennis (van andere afdelingen of ziekenhuizen, aanbieders en/of publicaties).

- … omarmt snel nieuwe mogelijkheden om onze patiënten van dienst te zijn.
- … herkent snel verschuivingen en ontwikkelingen in de zorg.
- … analyseert en interpreteert snel veranderende markteisen.
- … maakt regelmatig kleine aanpassingen aan onze bestaande zorgdienstverlening en zorgproducten.
- … verbetert jaarlijks de efficiëntie van onze interne processen en zorgdienstverlening.
- … breidt de zorgdienstverlening voor bestaande patiënten uit.
- … introduceert verbeterde (reeds bestaande) zorgdienstverlening en zorgproducten voor onze patiënten.
- Onze medische professionals gaan efficiënt te werk bij het uitvoeren van (poli)klinische activiteiten en onderzoeken.
- Professionals van onze afdeling hebben een duidelijk begrip van taken en verantwoordelijkheden.

Patient Service Peformance (PSP)
Patient Service Performance (PSP) betreft de mate waarin een ziekenhuisafdeling hoogwaardige zorgdiensten en -producten levert aan patiënten.

Onze afdeling:

Kies het toepasselijke antwoord voor elk onderdeel:
helemaal oneens – oneens - enigszins oneens – neutraal - enigszins eens – eens - helemaal mee eens

- ...vergroot de beschikbaarheid van medische diensten met behulp van digitale en/of datagedreven innovaties.
- … vergroot de toegankelijkheid van medische diensten met behulp van digitale en/of datagedreven innovaties.
- … verhoogt de kwaliteit van de medische dienstverlening met behulp van digitale en/of datagedreven innovaties.
- … verhoogt de patiënttevredenheid met behulp van digitale en/of datagedreven innovaties.
- … vergroot de samenwerking met patiënten met behulp van digitale en/of datagedreven innovaties.
- … verhoogt de loyaliteit van patiënten met behulp van digitale en/of datagedreven innovaties.
- … vergroot de reputatie van ons ziekenhuis in de markt door middel van digitale en/of datagedreven innovaties.
- … vergroot de erkenning van ons ziekenhuis in de markt met behulp van digitale en/of datagedreven innovaties.
- … verbetert de positie van ons ziekenhuis in de markt met behulp van digitale en/of datagedreven innovaties.

Appendix 3: Data Population (in Dutch)

Geef het type ziekenhuis aan waar u werkzaam bent:

Antwoord	Aantal	Percentage
Universitair Medisch Centrum (UMC)	10	9,34%
Samenwerkend Topklinisch opleidingsziekenhuis (STZ)	58	54,21%
Samenwerkend Algemeen Ziekenhuis (SAZ)	22	20,56%
Overig Algemeen Ziekenhuis (OAZ)	16	14,95%
Overig (oncologisch centrum)	1	0,93%

Geef het specialisme van uw afdeling aan:

Antwoord	Aantal	Percentage
Anesthesiologie	9	8,41%
Apotheek	2	1,87%
Cardiologie	8	7,48%
Cardiothoracale Chirurgie	0	0%
Chirurgie	15	14,02%
Dermatologie	2	1,87%
Endocrinologie	0	0%
Geriatrie	2	1,87%
Hematologie	1	0,93%
Immunologie	0	0%
Infectieziekten	0	0%
Intensive Care Volwassenen	6	5,61%
Intensive Care Kinderen	0	0%
Inwendige Geneeskunde	2	1,87%
Keel-, neus- en oorziekten	3	2,80%
Kindergeneeskunde	3	2,80%
Neonatologie	1	0,93%
Longziekten	4	3,74%
Maag-, darm en leverziekten	1	0,93%
Medische psychologie	5	4,67%
Mondziekten-kaakchirurgie/Ziekenhuistandheelkunde	1	0,93%
Neurochirurgie	0	0%
Neurologie	4	3,74%
Nierziekten	0	0%
Oncologie	2	1,87%
Oogheelkunde	2	1,87%
Orthopedie	10	9,35%
Plastische en Reconstructieve chirurgie	0	0%
Psychiatrie	0	0%
Reumatologie	1	0,93%
Revalidatie	1	0,93%

Antwoord	Aantal	Percentage
Spoedeisende hulp	1	0,93%
Sportgeneeskunde	0	0%
Urologie	3	2,80%
Vasculaire geneeskunde	0	0%
Verloskunde/Gynaecologie	6	5,61%
Overige	12	11,21%

Overige: Operatie kamers en Dagbehandeling, staf poliklinieken, poli management, management, dietetiek, maatschappelijk werk , geestelijke verzorging en medische psychologie, Chronische zorg, Radiologie, OK, Klinische Fysica, Radiotherapie, Bloedafname laboratorium.

Onze afdeling richt zich primair op:

Antwoord	Aantal	Percentage
Verzekerbare zorg	73	68,22%
Niet-verzekerbare zorg	3	2,80%
Allebei (ongeveer evenveel)	7	6,54%

Hoeveel artsen (fte) zijn werkzaam binnen uw afdeling (met arts wordt bedoeld medewerker met minimaal kwalificatie basisarts):

- Minimale waarde: 0
- Maximale waarde: 500
- Gemiddelde: 27,26

Hoeveel medewerkers (fte) zijn in totaal werkzaam binnen uw afdeling (inclusief ondersteunend en administratief):

- Minimale waarde: 0
- Maximale waarde: 2500
- Gemiddelde: 144

Geef aan hoelang uw afdeling bestaat in haar huidige vorm gezien vanuit de werkprocessen:

Antwoord	Aantal	Percentage
0-5 jaar	18	16,82%
6-10 jaar	23	21,50%
11-15 jaar	21	19,63%
16-20 jaar	10	9,35%
21-25 jaar	4	3,74%
25+ jaar	31	28,97%

Geef een benadering van het aantal patiënten aan dat uw afdeling jaarlijks bezoekt:

Antwoord	Aantal	Percentage
< 4.000	18	16,82%
4.000 – 6.500	6	5,61%
6.501 – 9.000	12	11,21%
9.001 – 11.500	14	13,08%

Antwoord	Aantal	Percentage
11.501 – 14.000	16	14,95%
> 14000	41	38,32%

Geef uw huidige functie binnen de organisatie aan:

Antwoord	Aantal	Percentage
Afdelingshoofd	11	10,28%
Teamleider	5	4,67%
Manager bedrijfsvoering	7	6,54%
Verpleegkundig specialist	3	2,80%
Physician assistant	0	0%
Chef de Clinique	3	2,80%
Arts (Specialist)	52	48,60%
AIOS	5	4,67%
ANIOS	1	0,93%
Overige	20	18,69%

Overige: Ziekenhuisapotheker, CPIO, IT, adviseur digitale dienstverlening, programma manager, verpleegkundige, Medisch Specialist en CMIO, Projectleider SPO en duurzame inzetbaarheid, Gz psycholoog, Orthoptist, Doktersassistent, Verpleegkundig endoscopist, Anesthesie medewerker, gespec verpleegkundige, GIOS, Gz-psycholoog, Radiotherapeutisch Laborant(MBB-er), specialist opleider bestuur.

Geef aan hoeveel jaar u op uw huidige afdeling werkt:

Antwoord	Aantal	Percentage
0–5 jaar	43	40,19%
6–10 jaar	18	16,82%
11–15 jaar	19	17,76%
16–20 jaar	13	12,15%
21–25 jaar	11	10,28%
25+ jaar	3	2,80%

Hoeveel jaar werkervaring heeft u na het afronden van uw opleiding als basisarts?

Antwoord	Aantal	Percentage
0–5 jaar	3	2,80%
6–10 jaar	9	8,41%
11–15 jaar	11	10,28%
16–20 jaar	16	14,95%
21–25 jaar	13	12,15%
25+ jaar	11	10,28%
n.v.t.	18	16,82%