MASTER'S THESIS

# Digital transformation in hospitals: improving patient service performance through innovation ambidexterity

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# Digital transformation in hospitals: improving patient service performance through innovation ambidexterity

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Abstract

Hospitals are in the midst of a major digital transformation. Dutch hospitals are leading in Europe when it comes to digitization. From a dynamic capabilities perspective, we see that hospitals need to innovate both exploitatively and exploratively at the same time in order to increase the service performance towards their patients. Hospitals use more and more specific apps and wearable sensors (Lightweight IT) and Big Data on department level.

Based on the results of a survey among 108 Dutch hospital departments, this research tests whether the use of Lightweight IT, together with Big Data Analytics Capabilities (BDAC) have a positive influence on Patient Service Performance via Innovation Ambidexterity. The hypotheses are tested using partial least squares structural equation modeling (PLS-SEM).

There is indeed a significant relationship between BDAC and Innovation ambidexterity and there is also a positive relationship between Innovation ambidexterity and Patient Service Performance. However, due to the strong effect of BDAC on Innovation Ambidexterity. No significant direct positive effect of Lightweight IT on Innovation Ambidexterity is demonstrated. The results can indicate the importance of BDAC for hospitals and the need to innovate exploitatively and exploratively to contribute to a higher service performance towards the patient.

# Key terms

Lightweight IT, Big data analytics capability, hospital, healthcare, innovation ambidexterity, Patient Service Performance, PLS-SEM, digital transformation

# Summary

Hospitals are in the midst of a digital transformation. Dutch hospitals are leading in Europe in the use of electronic patient records, digital prescription of medication, the use of patient apps and wearable sensors (so-called Lightweight IT) and the automation of clinical tasks. This also creates a wealth of data that can contribute to better decision-making, both in the hospital organization and towards the patient. The digital transformation requires hospitals to use dynamic capabilities to design new business models and adapt existing ones, such as the ability to innovate both exploitatively and exploratively. The use of Lightweight IT and Big Data Analytics should contribute to this innovation ambidexterity.

The study started with a literature review based on the formulated research questions. This was based on a number of baseline articles related to the main topics, which are Lightweight IT, Big Data Analytics Capabilities, Innovation Ambidexterity and Patient Service Performance. The topics have been further explored with reverse and forward snowballing. In addition, the building blocks method was used to find answers to the research questions.

The research shows that the use of Lighweight IT, in the form of department-specific patient apps and wearables, is necessary for innovation. Lightweight IT opposes the more traditional and already existing Heavyweight IT (servers and databases). On the one hand, they are opposed to each other, but both are needed to innovate. Deploying existing systems in a new way and new systems on new knowledge regimes leads to innovation ambidexterity.

The increase in the use of sensors and remote monitors also leads to a large increase in available data. The ability to make use of this Big Data offers hospitals the opportunity to discover new business values and insights. This improves the quality of care and patient service performance. But also on the business process side this has advantages for resource management and improved decision making. The questions about Big Data analytics are department-specific, which is why an organization must have the ability to adapt to this. Big Data Analytics Capabilities give hospitals the ability to enhance their dynamic capabilities, which has a positive influence on the innovation ambidexterity of the organization.

Innovation ambidexterity in turn can increase organizational performance. Organizational performance is a combination of financial and non-financial indicators that indicate how organizations can achieve their goals. For a hospital department, the non-financial indicators translate into patient service performance. The ability of a hospital department to innovate both operationally and exploratively will therefore have a positive influence on patient service performance.

Based on the theory, three hypotheses have been formulated in this study:

1. Hospital departments' use of modular lightweight clinical systems positively impacts innovation ambidexterity.
2. Hospital departments' big data analytics capabilities positively impact innovation ambidexterity
3. Hospital departments' innovation ambidexterity positively impacts the patient service performance.

These were tested by means of a survey among Dutch hospital departments. The respondents were approached on the basis of convenience sampling via email, telephone and social media. The data was collected from September to December 2021. After cleaning the data, 108 surveys were used for further data analysis. For the data analysis, partial least square structural equation modeling with the software tool SmartPLS was used.

After checking the internal consistency reliability, convergent validity and discriminant validity, the data turned out to be valid and reliable. Testing the structural model by bootstrapping provided evidence for the positive influence of Big Data Analytics Capabilities on Innovation ambidexterity and the positive influence of Innovation ambidexterity on Patient Service Performance. However, no evidence was found for the influence of Modular Lightweight Clinical Systems (MLCS) on Innovation ambidexterity. Closer analysis shows that this is due to the strong influence of BDAC on IA. From the perspective that the use of MLCS generates a lot of data and may have a direct influence on BDAC, this relationship was investigated and it turned out to be a strong relationship.

This research shows that hospitals must invest in innovation to increase patient service performance, a primary goal for every hospital. Hospitals must do this by innovating both exploitatively and exploratively. Important elements for this are BDAC and the use of MLCS. Much further research is needed, especially in the field of MLCS. Possible differences in the types of hospitals should also be investigated.

# Contents

# 1. Introduction

## 1.1. Background

Hospitals are fully engaged in a digital transformation, i.e. the use of digital resources to support the business processes in order to create value and develop new digital business models. According to a study by Deloitte (Taylor, Properzi, Bhatti, & Ferris, 2021), the Dutch healthcare system is ahead of digitization in many respects compared to other European countries. The Netherlands is at the top in terms of working with electronic patient files, digital prescription of medication, the use of patient apps and wearables and the automation of clinical tasks. According to the same study, Covid-19 has accelerated the digital transformation enormously especially the use of telehealth, such as virtual consultations and remote patient monitoring (Taylor et al., 2021).

We can define these patient apps and wearables as a new form of IT, namely lightweight IT. This in contrast to heavyweight IT. These are the traditional systems and databases, which are becoming increasingly sophisticated and expensive due to advanced integration (Bygstad, 2015). This lightweight IT plays an important role in the innovation of services for patients (Bygstad & Øvrelid, 2020).

Increasing digitization is also causing an enormous growth in available data. But to date, the healthcare industry has not fully recognized the potential benefits of big data analytics (Wang, Kung, & Byrd, 2018). While big data analytics can be an effective opportunity to gain benefits for the business (Wang et al., 2018). For hospitals, this may include optimal planning of care processes, the development of multidisciplinary care pathways and more insight into the effectiveness of certain treatment pathways.

This digital transformation leads to new business models and other organizational routines and managerial skills (van de Wetering, 2021c; van de Wetering, Hendrickx, Brinkkemper, & Kurnia, 2021). This leads for hospitals to the use of dynamic capabilities (Van de Wetering & Versendaal, 2021). These are the firm's ability to integrate, build and reconfigure internal competences to address, or in some cases to bring about, changes in the business environment (Teece, 2007; Teece, Pisano, & Shuen, 1997). The strength of a firm's dynamic capabilities is vital in many ways to its ability to maintain profitable over the long term, including the ability to design and adjust business models (Teece, 2018). The main focus of hospitals is not to be profitable, but profitability in this case can be seen as achieving a high service performance by delivering good quality of care to their patients.

The use of lightweight IT and big data analytics should contribute to one of the dynamic capabilities, i.e. the innovation ambidexterity of hospital departments. That is the balancing of exploitative and explorative innovation activities to achieve high-performance levels (Gibson & Birkinshaw, 2004; Jansen, Van Den Bosch, & Volberda, 2006). This means that hospitals must focus on both the exploration of innovation and the exploitation of innovation in order to ensure the delivery of high quality care to the patients, while controlling the costs of patient care delivery (Foglia, Ferrario, Lettieri, Porazzi, & Gastaldi, 2019). According to Gibson and Birkinshaw (2004), achieving long term success requires a dynamic capability enabling firms to satisfy current demands while simultaneously being prepared for tomorrow's developments.

This research focuses on the influence of “lightweight IT” (being crucial in the hospital practice to drive patient service innovations (Bygstad & Øvrelid, 2020)) and “big data analytics capabilities”, (leading to a higher quality of care in hospitals (Wang, Kung, Gupta, & Ozdemir, 2019)) on the innovation ambidexterity of hospital departments and to what extent this ultimately contributes to the service provided to the patient. Because a high quality of care services may further lay the foundation for building long-term relationships with patients. This high quality of care can be created by using healthcare service attributes, such as improving medical services for patients (Wu & Hu, 2012). Previous research focused on organizational level. An increasing complexity of care creates the need to organize innovations at department level. Because the patient population differs per department and therefore also the way of diagnosing, treating and guiding patients. The role that the use of lightweight IT and BDAC plays in this is therefore also department-specific.This research therefor will focus on department level of Dutch hospitals.

In chapter 1, the exploration of the topic is discussed in more detail, the problem definition and assignment formulation are discussed and the relevance of this research is discussed and the research approach is outlined. The theoretical framework is presented in chapter 2, followed by the research design in chapter 3. Chapter 4 describes the results, after which Chapter 5 concludes with the discussion, conclusions and recommendations for practice and possible follow-up research.

## 1.2. Exploration of the topic

The most relevant definitions within the study are explained in this section.

**Big data analytics**

According to Gandomi and Haider (2015), there is talk of "Big data" if it meets the 3Rs. These are volume, velocity and variety. Volume refers to the size of the available datasets, velocity refers to the speed at which data is generated, recorded, analysed and leads to decision-making, while variety refers to the structural heterogeneity of the datasets. A fourth V can also be added to this, namely veracity. This represents the unreliability inherent in some data sources (Gandomi & Haider, 2015). The analysis of this data is called big data analytics (BDA) and is used to support clinical decision-making; optimization of clinical operations and reduction of healthcare costs (Mehta & Pandit, 2018).

**Big data analytics capabilities**

Wang and Hajli (2017) describe big data analytics capability as the ability to acquire, store, process and analyse large amounts of health data in a variety of forms, and to provide users with meaningful information, enabling them to deliver business values and insights in a timely manner. The availability of high quality data and technology needs to be coupled with organizational routines and individual skills for an analytic capability (Shanks, Sharma, Seddon, & Reynolds, 2010). According to Gupta and George (2016), the big data analytics capability of an organization should consist out of tangible (data, technology, basic resources), human (managerial and technical skills) and intangible (data-driven culture, intensity of organizational learning) resources. To create a BDA capability, a firm needs not just one or two of these resources, but it is the unique combination of all three that generates a firm-specific BDA capability (Gupta & George, 2016).

**Innovation ambidexterity**
For an organization to become ambidextrous, they should develop exploratory and exploitative innovation simultaneously in different organizational units (Benner & Tushman, 2003; He & Wong, 2004). Exploratory innovation can be described as the pursuing of new knowledge and the development of new products and services for emerging customers and markets. Exploitative innovation on the other hand can be described as the building upon existing knowledge and the extending of existing products and services for the existing customers.
Božič and Dimovski (2019) conceptualize innovation ambidexterity as an organizational dynamic capability which encompasses the routines and processes that ambidextrous organizations rely on to allocate, mobilize, coordinate and integrate various contradictory innovative efforts.

**Heavyweight and lightweight IT**
Heavyweight IT is the traditional form of IT with software installed on computers and servers, and data that is stored in databases and is accessible through the client applications. According to Bygstad (2017), it is a knowledge regime, driven by IT professionals, made possible by systematic specification and proven digital technology and realized through software engineering. This form of IT is more focused on the back-end side and supports the documentation of work. It is usually managed by the IT department.

Lightweight IT, on the other hand, is the newer form of IT in the form of tablets, electronic whiteboards and mobile phones. According to Bygstad (2017) it is a knowledge regime, driven by the need of competent users for solutions, made possible by the consumerization of digital technology and realized through innovation processes. This is more focused on the front end by supporting work processes. Lightweight IT is often managed by the end users and suppliers.

According to Bygstad (2015), there are characteristic differences in heavyweight and lightweight IT in the areas of innovation and adoption. In terms of heavyweight IT, innovation mainly lies with IT professionals who combine systems and middleware. With lightweight IT, it is mainly the medical professionals who, together with suppliers, develop lightweight IT aimed at work tasks. The adoption of heavyweight IT usually stems from mandatory use and an organized implementation. With lightweight IT, use is voluntary, with increased adoption generating more resources for the solution (Bygstad, 2015).

**Service performance**
In hospitals service performance is based on the quality of care for patients (de Vries & Huijsman, 2011). According to Wu and Hu (2012), this hospital service performance can be seen in broader perspective as patient performance. Based on the Balanced ScoreCard (Kaplan & Norton, 2004) there are three indicators for patient performance, these are service attributes, patient relationship and hospital image. The service attributes are defined as the availability, accessibility and quality of medical services. Patient relationship is defined in terms of patient satisfaction, partnership with patients and the loyalty of patients. The hospital image defines the reputation, recognition and the market ranking of the hospital.

## 1.3. Problem statement

Hospitals are in a major digital transformation that has accelerated enormously due to Covid-19 (Taylor et al., 2021). One of the digital resources that plays a role in this is the emergence of lightweight IT (Bygstad, 2015). This poses challenges in terms of support from the IT department (Gartner, 2014) and governance around lightweight IT (Bygstad & Iden, 2017). In addition, digitization creates a wealth of data that can be used in decision-making processes through big data analytics (Wang et al., 2019). This requires certain capabilities required for big data analytics (Wang et al., 2019). The aim of these innovations is to increase service performance towards the patient (Wang et al., 2018) and to create new services for the patient (Bygstad, 2017).
But although healthcare providers have strong digital business ambitions, they must overcome a large capabilities gap (Gartner, 2018), for using lightweight IT en big data analytics in order to increase patient service performance.

## 1.4. Research objective and questions

Hospitals are increasingly using lightweight IT in the form of modular lightweight clinical systems and big data analytics. But are the right capabilities available for this? How can these capabilities be in balance between the explorative and exploitative innovation and thus contribute to the innovation ambidexterity of the hospital? And will this affect the patient service performance?
This leads to the question to what extent the use of modular lightweight clinical systems and the use of big data analytics capabilities can have an influence on the innovation ambidexterity of a hospital and to what extent this contributes to the service performance towards the patient.

For answering this, the following research questions have to be answered:

1. To what extent does the use of modular lightweight clinical systems have a positive influence on the innovation ambidexterity of a hospital?
2. To what extent do big data analytics capabilities have a positive influence on the innovation ambidexterity of a hospital?
3. What is the influence of innovation ambidexterity on the patient services performance of a hospital department?

## 1.5. Motivation/relevance

This study takes place in Dutch hospitals and focuses on the department level. With the limited numbers of hospitals in the Netherlands, the study on department levels gives the opportunity for a quantitative research with a sufficiently high sample rate. Most earlier studies within this area took place on organizational level or as qualitative research (Bygstad & Øvrelid, 2020; Ghosh & Scott, 2011), or not from a medical point of view (Božič & Dimovski, 2019; Wang et al., 2019).

The digitization of hospitals is a main theme within hospital organizations for several years, but this digitization has been accelerated by the Covid-19 pandemic. This digitization leads to new methods for patient diagnostics and treatment and is part of the digital transformation that takes places in hospitals at this moment (Gartner, 2018). But only with the right use of capabilities for using lightweight clinical systems and big data analytics, this digital transformation can succeed in higher levels of patient service performance. This research provides insights into the theories behind it and will test these theories at the hospital department level by means of quantitative research.

## 1.6. Main lines of approach

The research is generally conducted as follows:

The first step is a literature review. The core concepts of this research are examined in more detail and the relationships between these concepts. The result of this literature review are three hypotheses. The next step is to collect data to test the hypotheses. This data collection will be carried out by means of a survey. After that, the collected data will be analyzed using PLS-SEM, whereby the data will first be tested for validity and reliability. The model is then tested to find evidence for the hypotheses. Based on this, the conclusions are drawn.

# 2. Theoretical framework

This chapter provides the theoretical framework.

## 2.1. Research approach

The research focuses on several concepts, these are lightweight clinical systems, big data analytics capabilities, innovation ambidexterity and (patient) service performance. Starting point for this thesis is literature research based on baseline literature papers regarding the aforementioned concepts. From these papers backward and forward snowballing is applied to gather knowledge about the concepts. After this a more in depth investigation took place of the literature to find connections between the concepts. This resulted in the research questions in section 1.4. To answer the research questions, literature review took place based on the buildingblocks method, i.e. using queries of relevant keywords and synonyms in the online OU library (and in specific cases via EBSCO, AIS and Web of Science) and Google Scholar. When results exceeded 100 in the OU library, than the time span of the publication date is shortened and the keywords were expanded. The specific queries eventually used to answer the research questions are described in the next section.

## 2.2. Implementation

For research question 1 the online OU library (https://bibliotheek.ou.nl/) is used with the advanced search option (peer reviewed publications and articles from the last five years) and the following query: ("Modular lightweight clinical system" OR "lightweight IT" OR app OR wearable) AND (hospital OR healthcare OR "medical center" OR "medical institution") AND ("Innovation ambidexterity" OR "explorative innovation" OR "exploitative innovation" OR "organizational ambidexterity" OR "IT ambidexterity"). This led to a list of 45 results. These articles are then checked on relevance. A first check based on the title and brief results in the OU library search engine, led to seven articles for further investigation. These articles are then checked on relevance (does this research give any insights into Lightweight clinical systems and innovation ambidexterity?) by reading the abstract. Searches with the same query in EBSCO, AIS and WoS, did not lead to any new articles. Searching Google Scholar with the same query led to 334 results, of which one relevant article. In total the queries and relevance check led to seven articles that are used for the theoretical framework.

For research question 2 the online OU library (https://bibliotheek.ou.nl/) is used with the advanced search option (peer reviewed publications) and the following query: (BDA capabilities) AND (innovation ambidexterity). This led to a list of 10 results. The query ("dynamic capabilit*") AND (innovation ambidexterity) led to 4 results. These articles are then checked on relevance by a first quick check based on the title and brief results in the OU library search engine. This led to 8 articles for further investigation. These articles are then checked on relevance (does this research give any insights into BDA Capabilities or dynamic capablities and innovation ambidexterity?) by reading the abstract. Searches with the same query in EBSCO led to one relevant article, AIS and WoS, did not lead to any new articles. Searching Google Scholar with the same query led to 233 results, of which another four relevant articles (three of these articles where already part of the baseline literature. In total the queries and relevance check led to 8 articles that are used for the theoretical framework.

For research question 3 the online OU library (https://bibliotheek.ou.nl/) is used with the advanced search option (peer reviewed publications) and the following query: ("innovation ambidexterity") AND ("hospital" OR "healthcare") AND ("performance").

This led to a list of 58 results. These articles are then checked on relevance by a first quick check based on the title and brief results in the OU library search engine. This led to 8 articles for further investigation. These articles are then checked on relevance (does this research give any insights into innovation ambidexterity and service performance?) by reading the abstract. Searches with the same query in EBSCO, AIS and WoS, did not lead to any new articles. Searching Google Scholar with the same query led to 389 results, of which another 5 relevant articles (three of these articles where already part of the baseline literature. In total the queries and relevance check led to 7 articles that are used for the theoretical framework.

Based on these literature, the results and conclusion follow in the next section.

## 2.3. Results and conclusions

In this section, the research questions as described in section 1.4, will be answered based on scientific literature that was found.

### 2.3.1. Modular lightweight clinical systems and innovation ambidexterity

Seen from the digital transformation point of view within the hospitals, the use of IT should support the innovation in hospitals (Taylor et al., 2021), by the use of new technologies and knowledge regimes. Within hospitals we see the traditional use of heavyweight IT and the upcoming of lightweight IT (Bygstad, 2015). Lightweight IT is configurable and thus easier to adapt to particular processes, but it is also powerful in reconfiguring digital infrastructures to revitalise hidden information for the purpose of process innovation. Heavyweight IT, on the other hand, enables secure access to comprehensive information repositories. Consequently, both are needed in order to enable profound business innovation (Bygstad & Øvrelid, 2020). Bygstad (2015) states that the two domains are moving in opposite directions, but they are also complementary. Lightweight IT is to a large degree dependent on heavyweight IT as a platform and as a data repository. The reverse is less obvious, but still true: heavyweight IT is dependent on lightweight IT for innovation and organizational agility (Bygstad, 2015). With this, we make use of existing technology in an innovative way (i.e. the use of the digital infrastructure as a central foundation) and we also use new technology for exploring innovation (i.e. the use of lightweight IT to leverage core information and make it configurable on a user level (Bygstad & Øvrelid, 2020). The lightweight IT in hospitals is characterized by department specific patient apps and wearable sensors which are described as modular lightweight clinical systems (MLCS). These modular lightweight clinical systems make use of the already available central foundation, but use this in another way (exploitation) and in itself the lightweight clinical systems are based on new technologies with new knowledge regimes (exploration). This leads to the following hypotheses.

**Hypothesis 1:** *Hospital departments' use of modular lightweight clinical systems positively impacts innovation ambidexterity.*

### 2.3.2. Big data analytics capabilities and innovation ambidexterity

The increasing use of sensors and remote monitors in hospital departments leads to large amounts of data (Wang et al., 2018). To use this data in a way to increase quality of care and patient satisfaction, the use of Big Data Analytics Capabilities (BDAC) is needed (Wang et al., 2019). In a healthcare context, Wang et al. (2018) define big data analytics capability as the ability to acquire, store, process and analyze large amount of health data in various forms, and deliver meaningful information to users (physicians, nurses, hospital management) that allows them to discover business values and insights (e.g. improving quality of care, patient service improvement, better resource management, improved decision making and planning) in a timely fashion. The information needed can vary per department. Wamba et al. (2017) showed that BDAC have a positive influence on process-oriented dynamic capabilities, i.e. a firm's ability to change (improve, adapt or reconfigure) a business process better than the competition in terms of integrating activities, reducing cost, and capitalizing on business intelligence/learning (Gimun, Bongsik, Kyung Kyu, & Ho Geun, 2011; van de Wetering, 2021a, 2021b; Van de Wetering & Versendaal, 2021). Process capabilities are strengthened by improving professionals' knowledge resources. The professionals' learning and growth is important in building process capabilities. Especially in hospitals, where the professionals are knowledge workers for effectively raising the quality of care.(Wu & Hu, 2012). The learning capability of an organization facilitates innovation ambidexterity, by intraorganizational learning, interorganizational partnering, and an open organization culture (Lin, McDonough, Lin, & Lin, 2013). According to Božič and Dimovski (2019) the use of big data analytics is positively associated with the innovation ambidexterity, which enables firms to leverage external information and their knowledge-supporting innovation ability. BDACs enable firms to generate insight that can help strengthen their dynamic capabilities, which in turn positively impact incremental and radical innovation capabilities (Mikalef, Boura, Lekakos, & Krogstie, 2019).

This leads to the following hypothesis.

**Hypothesis 2:** *Hospital departments' big data analytics capabilities positively impact innovation ambidexterity*

### 2.3.3. Innovation ambidexterity and patient service performance

Fainshmidt, Pezeshkan, Lance Frazier, Nair, and Markowski (2016) show a positive relation between dynamic capabilities and organizational performance. They also demonstrate that higher-order dynamic capabilities, such as innovation ambidexterity (Božič & Dimovski, 2019) are more strongly related to organizational performance than lower-order dynamic capabilities. Winter (2003) defines lower–order dynamic capabilities as those effecting change in the resource base or ordinary capabilities and higher-order dynamic capabilities as those resulting from organizational learning which creates or modifies lower-order dynamic capabilities. Also Zang and Li (2017) and Božič and Dimovski (2019) demonstrate that innovation ambidexterity can create organizational performance gains. Firms which are committed to embracing digital technologies and improve their capability to better manage the digital technology are more likely to develop innovative digital solutions that in turn improve their organizational performance (Khin & Ho, 2019). Organizational performance can be defined as a set of both financial and non-financial indicators capable of assessing the degree to which organizational goals and objectives have been accomplished (Kaplan & Norton, 2005). The non-financial indicators in healthcare can be seen as the indicators for patient service performance (Wu & Hu, 2012), this is reflected in the availability, accessibility and quality of medical services, the loyalty and satisfaction of patients and the reputation, recognition and position of the hospital in the market. In healthcare this is the patient service performance that is reflected by the patient service, patient relation and the hospital image (Voelker, Rakich, & French, 2001; Zelman, Pink, & Matthias, 2003).

The above leads to the following hypotheses:

**Hypothesis 3:** *Hospital departments' innovation ambidexterity positively impacts the patient service performance.*

These hypotheses lead to the following conceptual model (Figure 1).

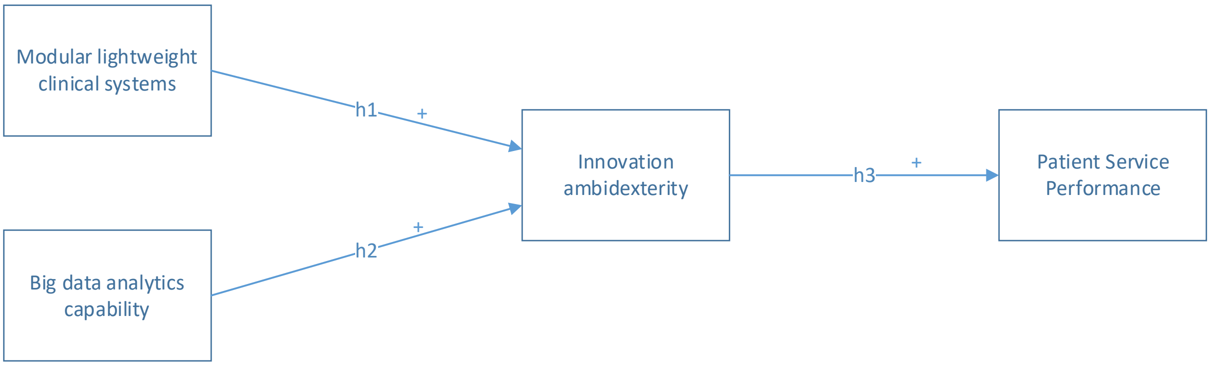


*Figure 1 Conceptual model*

## 2.4. Objective of the follow-up research

This research will contribute to the insight into the use of Modular Lighweight Clinical Systems (MLCS) and to what extent Big Data Analyitics Capabilities (BDAC) is present in Dutch hospitals and the extent to which these contribute to the innovation capacity of hospitals. In addition, insight will be gained into the extent that innovation ambidexterity contributes to patient service performance. These concepts have been theoretically substantiated, but have not previously been tested in this form by means of quantitative research. In addition, there is the practical relevance of the accelerated digital transformation in which hospitals find themselves (partly accelerated by Covid-19) and the need for the use of modular lightweight clinical systems and BDAC in order to be able to innovate. In order to test the hypotheses, survey research among Dutch hospital departments will investigate to what extent they make use of lighweight clinical systems and BDAC and to what extent they innovate in both an exploitative and explorative way. In addition, the patient service performance (PSP) is mapped on the basis of the use of medical services, the patient relationship and hospital image.

# 3. Methodology

In this section, substantiation is provided for the empirical research that is conducted.

## 3.1. Conceptual design: research method

This part of the research aimed to find empirical evidence for the hypotheses as described in section 2.3. For hypothesis testing a large set of quantitative data is necessary. The most common method for data collection, in this case, is the use of survey research (Saunders, Lewis, & Thornhill, 2019). The research focused on the use of lightweight IT clinical systems and the use of big data analytics capabilities within hospitals. This research has been carried out at the department level because of the increase in the complexity of care and the need that arises to organize these specific innovations that are required for this at the departmental level. There are only 69 hospitals in the Netherlands (Rijksoverheid, 2021), but with an average of more than thirty departments, this led to a sufficient sample size to retain sufficient valid response for the data analysis. The target population consisted of specialists, trainee specialists, specialist nurses and nurse practitioners, (clinical) department heads and managers of departments with patient contact. These respondents were the foremost respondents, at department level, who can provide insights into situations where medical knowledge is needed, enabling a unique treatment course (Wu & Hu, 2012). In addition, they have active contact with patients or have a good understanding of patient interactions and IT usage of the department.

## 3.2. Technical design: elaboration of the method

### 3.2.1. Data collection

The survey data was collected through convenience sampling. This is a type of non-probability sampling method where the sample is taken from a group of people easy to contact or to reach (Saunders et al., 2019). The respondents were approached by six master students through their network. Initially, the respondents were invited by mail and/or social networks. A week after the first contact, the respondents who not yet had responded were called back or reminded via e-mail or social networks. An overview of the used messages can be found in Appendix 1. The data was collected during a period of ten weeks.

The survey was checked and pretested several times by the six master students and three potentially respondents (neonatologist (CMIO), nurse specialist and head department of dermatology), to improve both the content and face validity of the survey items. The feedback has been processed.

To meet the criterion of reliability a minimal sample size of 90 was required, based on a statistical power of 80% with two independent variables, a significance level of 5% and a minimum $R^2$ of 0.10 (Cohen, 1992).

### 3.2.2. Measures and items

The constructs MLCS and BDAC were measured by using multiple reflective indicators. By this the measure of the construct will be more accurate than using a single item. Innovation ambidexterity was operationalized by explorative innovation and exploitaive innovation, since innovation ambidexterity involves achieving a balance between these two types of innovation. For creating the innovation ambidexterity construct, the explorative and exploitative innovation items can be summed, subtracted or multiplied (Junni, Sarala, Taras, & Tarba, 2013).

In this study, Gibson and Birkinshaw (2004) is followed with the argument that explorative and exploitative innovation are nonsubstitutable and interdependent, therefor the items were multiplied.

PSP is a higher order formative-formative type construct which is operationalized at a higher order of abstraction. PSP was measured by the first-order constructs Service, Patient Relation and Hospital image. Using this higher order construct reduces the number of relationships in the structural model (Ringle, Sarstedt, & Straub, 2012).

Lightweight IT is a new construct, the indicators to measure this construct are based on prior scientific research. (Tarenskeen, van de Wetering, Bakker, & Brinkkemper, 2020; Van de Wetering, 2019; Van de Wetering, Versendaal, & Walraven, 2018; Van de Wetering & Versendaal, 2020). All other indicators are used in prior scientific research to measure the specific constructs for BDAC (Yu, Zhao, Liu, & Song, 2020), innovation ambidexterity (Božič & Dimovski, 2019; Foglia et al., 2019; Jansen, Tempelaar, Van den Bosch, & Volberda, 2009) and patient service performance (Wu & Hu, 2012).

The indicators were measured using a 7-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree). This is commonly used in this type of empirical survey studies. The total survey is included in Appendix 2.

## 3.3. Data analysis

To get a general impression of the respondents and the hospital departments, descriptive statistics is used. For analysing the structural model, partial least square structural equational modelling (PLS-SEM) is used. PLS-SEM is very useful for models with higher-order variables (Hair, Sarstedt, Ringle, & Mena, 2011; Ringle et al., 2012). Another benefit of PLS-SEM is that it does not necessarily require normal distribution and is suitable for small sample sizes (Hair Jr, Hult, Ringle, & Sarstedt, 2016; Reinartz, Haenlein, & Henseler, 2009). All analysis are carried out with the software tool SmartPLS version 3.3.5 (Ringle, Wende, & Becker, 2015).

For assessing the results with the PLS algorithm, the basic settings are used:

- weighting scheme: path (recommended approach)
- maximum iterations: 2000 (generally used number. Should be sufficiently large)
- stop Criterion (10^-X): 7 (default setting 10^-7, this value should be sufficiently small)

To determine the quality of the measurement model, the following metrics are used. The treshhold levels that are used in the data analysis of the results are explained below.

**Internal consistency reliability (Cronbach's Alpha, Composite Reliability)**

Cronbach's Alpha is the more conservative measure of reliability, as composite reliability tends to overestimate the internal consistency reliability. The true reliability lies between Cronbach's alpha (lower bound) and Composite reliability (upper bound) (Hair Jr et al., 2016). The values for both indicators are seen as satisfactory between 0.7 and 0.9. Values above 0.95 are not desirable because this means that all the indicators measure the same phenomenon (Hair Jr et al., 2016).

**Convergent validity (Average Variance Extracted)**

Outer loadings of at least 0.708 are considered good, while the square of the outer loadings represents how much variation in an item is explained by the construct. This should be more than 50%, thus leading to a score of 0.5, which is the square of 0.708. Mostly 0.7 is considered as close enough to 0.708 (Hair Jr et al., 2016). Loadings lower than 0.4 should always be deleted. Indicators with loading between 0.4 and 0.7 are only deleted from the model when deletion leads to an increase in the composite reliability above the suggested threshold level or are retained on their basis for contribution to content validity (Hair Jr et al., 2016).

In the same way as the individual indicators, an AVE score of at least 0.5 explains that, on average, the construct explains more than half of the variance of its indicators (Hair Jr et al., 2016).

**Discriminant validity (Cross loadings, Fornell-Larcker criterion, Heterotrait-Monotrait ratio).**

Cross loadings will be checked, where the outer loading of the indicator on the associated construct must be greater than the loading on any other construct. This proves that these indicators only measure the associated construct and are discriminant. As rule of thumb a minimum difference of 0.02 will be used.

Fornell-Larcker criterion shows that a construct shares more variance with its associated indicators than with any other construct. This is done by checking if the square root of each constructs AVE is greater than its highest correlation with any other construct.

The Heterotrait-Monotrait (HTMT) ratio is the estimate of the true correlation between two constructs in case they were measured perfectly. If this true correlation is close to 1, there is a lack of discriminant validity.

**Assessing the PLS-SEM structural model results**

First the path coefficients are determined, they have standardized values between approximately -1 and +1. The closer the patch coefficient is to 0, the weaker the relationship. With bootstrapping the empirical t values and p values are calculated. The coefficient is statistically significant when the t value is larger than the critical value. A commonly used critical value in a two-tailed test and significance level of 5% is 1,96. The p value should be smaller than 0,05 at a significance level of 5% for concluding that the relationship is significant.

The evaluation of the structural model is done with $R^2$ (explained variance), $f^2$ (effect size) and $Q^2$ (predictive relevance). The $R^2$ value can range from 0 to 1, there are no generally used rules of thumb whether a value can be considered as high. In addition the effect size ($f^2$) will be measured. Cohen (2013) indicates values for $f^2$ of 0,02, 0,15 and 0,35 respectively as small, medium and large effects. Whereas a value lower than 0,02 indicates that there is no effect.

To measure the predictive relevance of the model, the $Q^2$ value is calculated via blindfolding, using the cross-validate redundancy check as recommended for PLS-SEM. As omission distance D, a number between 5 and 10 is recommended (Hair Jr et al., 2016), where the number of records divided by D cannot be an integer. Then the same values would be removed on every run. Models with $Q^2$ values larger than 0 are considered as having predictive relevance.

## 3.4. Ethical aspects

All respondents were approached on a voluntary basis to participate in this study. There is no financial or other incentive for respondents to participate in this survey. There were no stakeholders from the target group who had a say in the design or implementation of this study. In addition, the respondents were able to complete the survey completely anonymously. The results of the research cannot be traced back to individual persons. There was the option to leave an email address to receive the results. If respondents did this, this was completely voluntary and the purpose for this was clearly stated. The e-mail addresses were not used in the analysis of the data and will only be used to inform respondents about the results of the survey. Furthermore, no options were included in the survey with which respondents could possibly be traced. To the best of our knowledge, there can be no possible damage with regard to the scientific, social and educational relevance of the research.

# 4. Results

In this section, the survey results are presented. First the data collection and examination is outlined, then the validity and reliability of the data is checked and last the model is tested.

## 4.1. Data collection and data examination

In the period of September until December 2021 in a period of ten weeks, the data is collected through survey research. A total of 334 started filling in the survey. From this group, 112 fully answered all the questions. The partially filled in surveys are checked with a missing value percentage of 10%. None of the partially filled in surveys met these criteria. The 112 surveys are then checked on any inconsistency. This led to four surveys that were obviously not answered from department level. In the further analysis of the data, 108 surveys are used. All questions are asked in the same way, so there is no need to flip the scales. Furthermore there are no suspicious response patterns of outliers detected. A step-by-step in depth explanation of the construction of the used data file from the RAW data file extracted from limesurvey is described in Appendix 3. A Sample size of 108 meets the criterium of a minimum sample size of 90 as described in section 3.4.

Most of the repondents work in a collaborative top clinical hospital (54%), 9% work in an University Medical Center, 35% in general hospitals en 2% in other types. The two other hospitals are an oncological center and a general practice[1]. Other demographic factors are shown in Table 1.

| **Element** | **Category** | **Frequency** | **Percentage** |
|---|---|---|---|
| Hospital type | University Medical Center | 10 | 9% |
| | Collaborative Top Clinical Teaching Hospital | 58 | 54% |
| | Collaborative General Hospital | 22 | 20% |
| | Other General Hospital | 16 | 15% |
| | Other | 2 | 2% |
| Department age | 0-5 years | 18 | 17% |
| | 6-10 years | 23 | 21% |
| | 11-15 years | 21 | 19% |
| | 16-20 years | 11 | 10% |
| | 21-25 years | 4 | 4% |
| | 25+ years | 31 | 29% |
| Amount of patients | < 4.000 | 18 | 17% |
| | 4.000 – 6.500 | 6 | 6% |
| | 6.501 – 9.000 | 13 | 12% |
| | 9.001 – 11.500 | 14 | 13% |
| | 11.501 – 14.000 | 16 | 15% |
| | > 14000 | 41 | 38% |
| Years working in department | 0-5 years | 44 | 41% |
| | 6-10 years | 18 | 17% |
| | 11-15 years | 19 | 18% |
| | 16-20 years | 13 | 12% |
| | 21-25 years | 11 | 10% |
| | 25+ years | 3 | 3% |

*Table 1 Demographics of respondents*

[1] The general practice is not a type of hospital. This record has been missed in the data cleanup process, but was only noticed after the data analysis. Deleting this record would not affect the overall outcome of the research, therefore it has been decided not to delete this record.

Most respondents (49%) are medical doctors, followed by department heads (10%). The other respondents are residents (6%), business managers (6%), team leads (5%), nursing specialists (3%), Chef de Clinique (3%) and other (19%). The top ten departments where respondents are working are Surgery (14%), Orthopedics (9%), Anesthesiology (8%), Cardiology (7%), Intensive Care Adults (6%), Obstetrics/Gynecology (6%), Medical Psychology (5%), Lung diseases (4%), Neurology (4%) and Pediatrics (3%).

The average amount of doctors working within the department is 17.2. For this calculation all amounts above 100 are not included in the calculation. We can assume that this is answered on hospital level instead on department level. The average amount of employees within the department is 69.5. For calculating this average, all values above 500 are not taken into account while we can assume that this is not on department level.

## 4.2. Model estimation and the PLS-SEM algorithm

The data is imported in the SmartPLS tool without any errors and missing values. After that, the path model was built in accordance with the conceptual model as described in section 2.3 (Figure 2) for assessing the results of the reflective measurement model. Patient Service Performance is a higher order construct that is built upon the constructs Service, Patient Relation and Hospital Image.

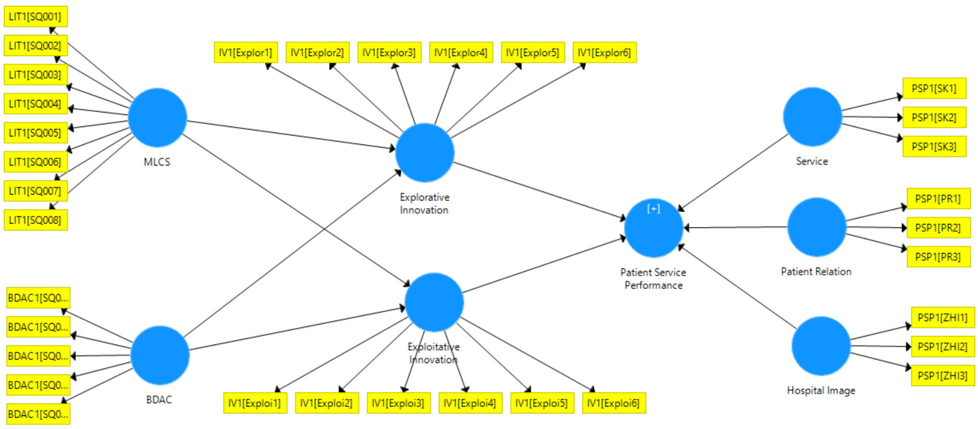


*Figure 2 Initial path model*

## 4.3. Outer loadings and path coefficients

Running the PLS algorithm leads to the following loadings (Figure 3).

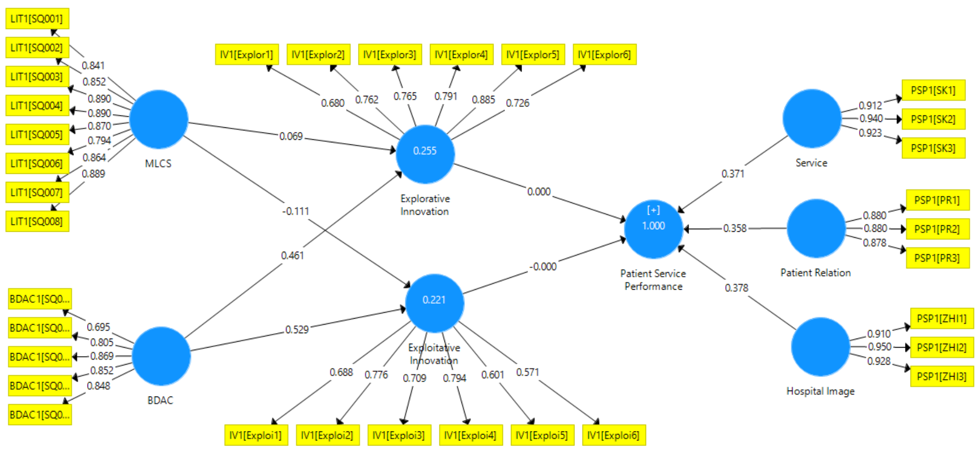


*Figure 3 Initial loadings*

Most reflective indicators have a loading of near 0.7 or higher and do not exceed 0.96. Exception are IV1[Exploi5] and IV1[Exploi6] that measure the Exploitative Innovation construct. First deleting IV1[Exploi6] (lowest loading) leads to an even lower loading for IV1[Exploi5]. Deleting IV1[Exploi5] and IV1[Exploi6] leads to loadings within the margins as described before in section 3.3 (Figure 4). Loadings of at least 0.708 are considered as good, while the square of the outer loadings represents how much of the variation in an item is explained by the construct. This should be more than 50%, thus leading to a score of 0.5, which is the square of 0.708. Mostly 0.7 is considered as close enough to 0.708. Loadings lower than 0.4 should always be deleted. Indicators with loading between 0.4 and 0.7 are only be deleted from the model when deletion leads to an increase in the composite reliability above the suggested threshold level or are retained on their basis for contribution to content validity (Hair Jr et al., 2016). The path coefficients of explorative innovation and exploitative innovation are 0.000 in this case and the $R^2$ of Patient Service Performance is 1.000. In this case all the variance is logically explained by the first order constructs which form the second order formative construct Patient Service Performance. For calculating the effects of the Explorative and Exploitative Innovation the latent variable scores need to be used for the constructs that we want to test. This is done in section 4.6 where we test the hypotheses.

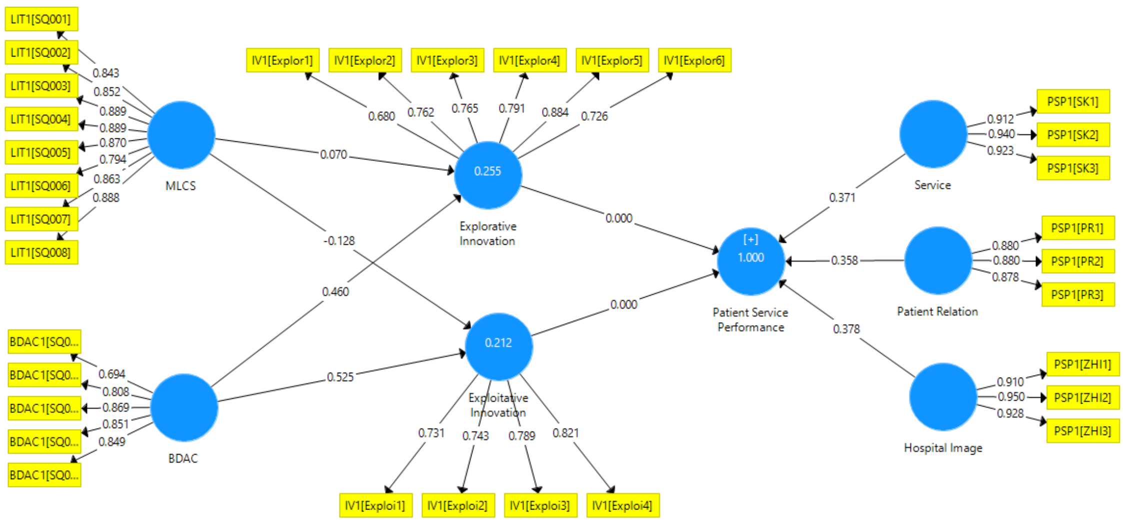


*Figure 4 Final loadings*

## 4.4. Construct Reliability and Validity

Based on the scores for Cronbach's Alpha, Composite Reliability and Average Variance Extracted, the model is reliable and valid (Table 2). Cronbach's alpha and composite reliability are above 0.7 for all constructs. The AVE score is above 0.5 for all the constructs. This could be expected as all the loadings were above of near 0.7 and the square of this is at least 0.49.

| | Cronbach's Alpha | Composite Reliability | Average Variance Extracted (AVE) |
|---|---|---|---|
| BDAC | 0.874 | 0.909 | 0.667 |
| Exploitative Innovation | 0.776 | 0.855 | 0.596 |
| Explorative innovation | 0.861 | 0.897 | 0.594 |
| Hospital Image | 0.921 | 0.950 | 0.864 |
| MLCS | 0.951 | 0.958 | 0.742 |
| Patient Relation | 0.853 | 0.911 | 0.773 |
| Service | 0.916 | 0.947 | 0.856 |

*Table 2 Construct reliability and validity*

## 4.5. Discriminant validity

First, the cross-loadings are checked to assess the discriminant validity. This results in the loadings as shown in Table 3. All outer loadings of the associated construct are greater than any outer cross-loadings on the other constructs and meets the requirements.

| | Big Data Analytics Capabilities | Exploitative Innovation | Explorative innovation | Lighweight IT | Patient Relation | Service | Hospital Image |
|---|---|---|---|---|---|---|---|
| BDAC1[SQ001] | **0.694** | 0.304 | 0.432 | 0.417 | 0.177 | 0.302 | 0.319 |
| BDAC1[SQ002] | **0.808** | 0.276 | 0.362 | 0.417 | 0.242 | 0.293 | 0.389 |
| BDAC1[SQ003] | **0.869** | 0.361 | 0.367 | 0.511 | 0.296 | 0.320 | 0.364 |
| BDAC1[SQ004] | **0.851** | 0.490 | 0.467 | 0.534 | 0.427 | 0.397 | 0.527 |
| BDAC1[SQ005] | **0.849** | 0.353 | 0.396 | 0.544 | 0.392 | 0.385 | 0.421 |
| IV1[Exploi1] | 0.162 | **0.732** | 0.562 | -0.033 | 0.326 | 0.406 | 0.347 |
| IV1[Exploi2] | 0.500 | **0.743** | 0.587 | 0.289 | 0.378 | 0.495 | 0.363 |
| IV1[Exploi3] | 0.302 | **0.789** | 0.540 | 0.086 | 0.479 | 0.455 | 0.495 |
| IV1[Exploi4] | 0.355 | **0.821** | 0.664 | 0.175 | 0.311 | 0.439 | 0.311 |
| IV1[Explor1] | 0.314 | 0.500 | **0.680** | 0.281 | 0.421 | 0.451 | 0.381 |
| IV1[Explor2] | 0.394 | 0.525 | **0.762** | 0.196 | 0.382 | 0.531 | 0.288 |
| IV1[Explor3] | 0.440 | 0.511 | **0.765** | 0.283 | 0.447 | 0.499 | 0.383 |
| IV1[Explor4] | 0.332 | 0.664 | **0.791** | 0.165 | 0.404 | 0.464 | 0.429 |
| IV1[Explor5] | 0.473 | 0.659 | **0.884** | 0.316 | 0.447 | 0.487 | 0.416 |
| IV1[Explor6] | 0.344 | 0.663 | **0.726** | 0.349 | 0.395 | 0.378 | 0.447 |
| LIT1[SQ001] | 0.555 | 0.281 | 0.419 | **0.843** | 0.342 | 0.282 | 0.346 |
| LIT1[SQ002] | 0.504 | 0.097 | 0.203 | **0.852** | 0.206 | 0.128 | 0.193 |
| LIT1[SQ003] | 0.501 | 0.150 | 0.251 | **0.889** | 0.249 | 0.135 | 0.219 |
| LIT1[SQ004] | 0.471 | 0.094 | 0.269 | **0.889** | 0.243 | 0.079 | 0.152 |
| LIT1[SQ005] | 0.497 | 0.155 | 0.307 | **0.870** | 0.336 | 0.176 | 0.314 |
| LIT1[SQ006] | 0.516 | 0.152 | 0.218 | **0.794** | 0.262 | 0.151 | 0.247 |
| LIT1[SQ007] | 0.525 | 0.097 | 0.233 | **0.863** | 0.267 | 0.184 | 0.257 |
| LIT1[SQ008] | 0.530 | 0.152 | 0.343 | **0.888** | 0.266 | 0.135 | 0.207 |
| PSP1[PR1] | 0.367 | 0.463 | 0.477 | 0.214 | **0.880** | 0.797 | 0.640 |
| PSP1[PR2] | 0.320 | 0.424 | 0.475 | 0.365 | **0.880** | 0.604 | 0.580 |
| PSP1[PR3] | 0.329 | 0.407 | 0.475 | 0.289 | **0.877** | 0.577 | 0.647 |
| PSP1[SK1] | 0.332 | 0.558 | 0.575 | 0.150 | 0.647 | **0.913** | 0.616 |
| PSP1[SK2] | 0.391 | 0.500 | 0.541 | 0.227 | 0.733 | **0.940** | 0.672 |
| PSP1[SK3] | 0.444 | 0.575 | 0.574 | 0.166 | 0.714 | **0.923** | 0.690 |
| PSP1[ZHI1] | 0.428 | 0.503 | 0.510 | 0.207 | 0.654 | 0.703 | **0.910** |
| PSP1[ZHI2] | 0.465 | 0.452 | 0.485 | 0.253 | 0.705 | 0.662 | **0.950** |
| PSP1[ZHI3] | 0.516 | 0.432 | 0.415 | 0.361 | 0.615 | 0.623 | **0.928** |

*Table 3 Cross loadings*

Checking the Fornell-Larcker criterion (Table 4) shows that its square root of each constructs AVE is greater than its highest correlation with any other construct and therefore meets the requirements.

| | Big Data Analytics Capabilities | Exploitative Innovation | Explorative innovation | Hospital Image | Lighweight IT | Patient Relation | Service |
|---|---|---|---|---|---|---|---|
| BDAC | **0.817** | | | | | | |
| Exploitative Innovation | 0.449 | **0.772** | | | | | |
| Explorative innovation | 0.502 | 0.761 | **0.771** | | | | |
| Hospital Image | 0.504 | 0.497 | 0.507 | **0.930** | | | |
| MLCS | 0.600 | 0.187 | 0.346 | 0.293 | **0.862** | | |
| Patient Relation | 0.387 | 0.492 | 0.541 | 0.709 | 0.326 | **0.879** | |
| Service | 0.422 | 0.588 | 0.609 | 0.713 | 0.197 | 0.756 | **0.925** |

*Table 4 Fornell-Larcker Criterion*

The last check for discriminant validity is done by measuring the HTMT ratio (Table 5). The value close to 1 relates to the relationship between exploitative and explorative innovation. As an extra check for the last relationship, a bootstrapping with 5000 samples has been added. This gave an average value of 0.935. The upper bounds of 97.5% do show a value of 1.008. But due to the fact that we are looking for the innovation ambidexterity, in which we expect an interaction between explorative and exploitative innovation, we consider the value found to be sufficient.

| | Big Data Analytics Capabilities | Exploitative Innovation | Explorative innovation | Hospital Image | Lighweight IT | Patient Relation |
|---|---|---|---|---|---|---|
| BDAC | | | | | | |
| Exploitative Innovation | 0.506 | | | | | |
| Explorative innovation | 0.569 | 0.934 | | | | |
| Hospital Image | 0.554 | 0.580 | 0.570 | | | |
| MLCS | 0.646 | 0.227 | 0.358 | 0.301 | | |
| Patient Relation | 0.435 | 0.592 | 0.631 | 0.797 | 0.353 | |
| Service | 0.464 | 0.689 | 0.687 | 0.775 | 0.196 | 0.847 |

*Table 5 Heterotrait-Monotrait Ratio (HTMT)*

## 4.6. Testing the hypotheses

From the above tests we see the data and constructs are reliable and valid. The next step is examining the relationships in the model and the predictive capabilities of the model. For building the model that must be tested as described in section 2.3, the innovation ambidexterity construct has to be created by multiplying the explorative innovation indicators (IV1[Explor1] to IV1[Explor6]) with the exploitative innovation indicators (IV1[Exploi1] to IV1[Exploi4]) which have a loading of at least 0.7. This leads to 24 indicators for the innovation ambidexterity construct. As mentioned in section 4.3, for showing the accurate scores for the relationships, the individual items of the constructs have to be replaced by the latent variable scores for the constructs that where gathered with running the PLS algorithm on the model. Then running the complete bootstrap procedure results in the model on the next page (Figure 5).

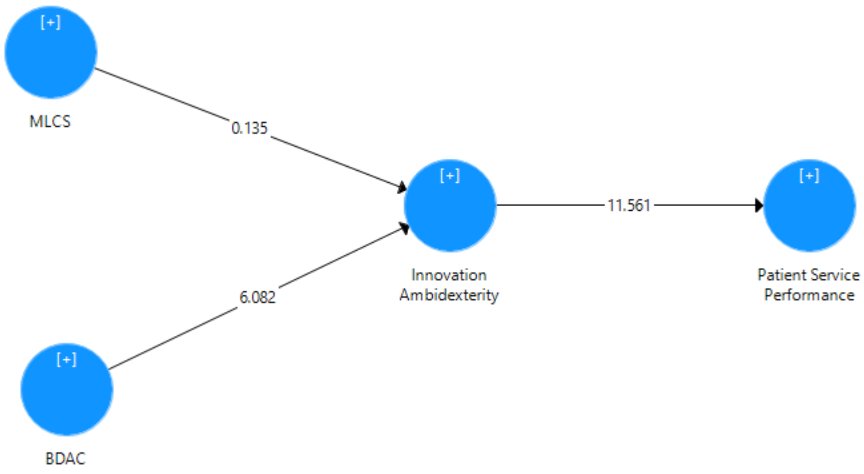

*Figure 5 Structural model T Values*

Table 6 gives an overview of the computed path coefficients, T values and P values as a result of the bootstrapping procedure. This shows strong relations between BDAC and Innovation ambidexterity and between Innovation ambidexterity and Patient Service Performance as expected based on the literature. Remarkably there is no strong relation between Lighweight IT and Innovation ambidexterity. This can be due to the strong relationship between BDAC and Innovation ambidexterity. When we run a bootstrap without the relationship BDAC and Innovation ambidexterity, then we see a T value of 3.454, with a P value of 0.001. This shows that without the connection between BDAC and Innovation ambidexterity, there is a significant statistical relation between MLCS and Innovation ambidexterity. From the point of view that the use of MLCS generates data that can influence BDAC, the relationship between MLCS and BDAC has been included in the model. This results in the values in Table 7.

| | Path coefficient Original Sample | Path coefficient Sample Mean | Standard Deviation | T Statistics | P Values |
|---|---|---|---|---|---|
| BDAC -> Innovation ambidexterity | 0.545 | 0.544 | 0.090 | 6.082 | 0.000 |
| MLCS -> Innovation ambidexterity | -0.013 | -0.018 | 0.097 | 0.138 | 0.890 |
| Innovation Ambidexterity -> Patient Service Performance | 0.646 | 0.645 | 0.057 | 11.365 | 0.000 |

*Table 6 Path coefficient, T and P values initial model*

| | Path coefficient Original Sample | Path coefficient Sample Mean | Standard Deviation | T Statistics | P Values |
|---|---|---|---|---|---|
| BDAC -> Innovation ambidexterity | 0.537 | 0.534 | 0.070 | 7.644 | 0.000 |
| MLCS -> BDAC | 0.599 | 0.599 | 0.068 | 8.777 | 0.000 |
| Innovation ambidexterity -> Patient Service Performance | 0.646 | 0.646 | 0.056 | 11.526 | 0.000 |

*Table 7 Path coefficient, T and P values modified test model*

Based on these results we must decline hypothesis 1, as there is no statistically significant relationship in the initial model.

**Hypothesis 1:** *Hospital departments' use of modular lightweight clinical systems positively impacts innovation ambidexterity.*

For hypothesis 2 en hypothesis 3, there is a statistically significant relationship and thus these hypotheses can be accepted.

**Hypothesis 2:** *Hospital departments' big data analytics capabilities positively impact innovation ambidexterity.*

**Hypothesis 3:** *Hospital departments' innovation ambidexterity positively impacts the hospital's service performance.*

As a measure for the predictive power, the $R^2$ values are calculated and presented in Table 8, thus can be concluded that the model has predictive power. In addition the effect size $f^2$ is presented in Table 9, this leads to the conclusion that there is no effect measured for the relation MLCS and Innovation ambidexterity, the effect of the relation BDAC and innovation ambidexterity is between medium and large and the effect of the relation of Innovation ambidexterity and Patient Service Performance is large.

| | Original Sample $R^2$ | Sample Mean $R^2$ | Standard Deviation | T Statistics | P Values |
|---|---|---|---|---|---|
| Innovation ambidexterity | 0.288 | 0.294 | 0.075 | 3.859 | 0.000 |
| Patient Service Performance | 0.417 | 0.418 | 0.073 | 5.724 | 0.000 |

*Table 8 R square values*

| | Original Sample $f^2$ | Sample Mean $f^2$ | Standard Deviation | T Statistics | P Values |
|---|---|---|---|---|---|
| MLCS -> Innovation ambidexterity | 0.000 | 0.009 | 0.013 | 0.012 | 0.990 |
| BDAC -> Innovation ambidexterity | 0.267 | 0.280 | 0.113 | 2.373 | 0.018 |
| Innovation ambidexterity -> Patient Service Performance | 0.716 | 0.746 | 0.226 | 3.161 | 0.002 |

*Table 9 f square effect size*

To determine the predictive relevance of the model, blindfolding is executed. The omission distance D is set to 7. This leads to $Q^2$ values of larger than 0 (Table 10), thus can be concluded that the model has predictive relevance.

| | $Q^2$ (=1-SSE/SSO) |
|---|---|
| Innovation ambidexterity | 0.257 |
| Patient Service Performance | 0.406 |

*Table 10 Q square values*

## 4.7. Multi Group Analysis

From the viewpoint that adoption of new kinds of technology is faster in knowledge intensive environments we want to search for a perhaps different relation between MLCS and innovation ambidexterity depending on the type of hospital, using non-parametric Multi -Group Analysis (MGA) (Henseler, Ringle, & Sinkovics, 2009). The most knowledge intensive hospitals are the University Medical Centers, but since the minimum group size must be 25 cases to be able to make a comparison (Hair Jr et al., 2016), it is not possible to compare this group to the other hospitals.

Then the second foremost option is to compare the Collaborative Top Clinical teaching (CTCT) hospitals and University Medical Centres (UMC) (63%) with the other hospitals (37%). The results from the MGA based on hospital type are shown in Table 11.

This in general shows no significant differences for the two groups. For the group of UMC's and CTCT hospitals we see even slightly lower scores for path coefficient and t value for the relation between MLCS and Innovation ambidexterity, but all are not significant and also the p value is not close to 0.

| | **CTCT hospitals and UMC's (63%)** | **Other hospitals (37%)** |
|---|---|---|
| **MLCS -> Innovation ambidexterity** | | |
| Path coefficients original | -0.058 | 0.117 |
| Path coefficients Mean | -0.064 | 0.120 |
| STDEV | 0.127 | 0.166 |
| t-value | 0.454 | 0.705 |
| p-value | 0.650 | 0.481 |
| **BDAC -> Innovation ambidexterity** | | |
| Path coefficients original | 0.524 | 0.530 |
| Path coefficients Mean | 0.525 | 0.506 |
| STDEV | 0.120 | 0.158 |
| t-value | 4.375 | 3.347 |
| p-value | 0.000 | 0.001 |
| **Innovation ambidexterity -> Patient** | | |
| Path coefficients original | 0.650 | 0.624 |
| Path coefficients Mean | 0.649 | 0.615 |
| STDEV | 0.062 | 0.114 |
| t-value | 10.525 | 5.492 |
| p-value | 0.000 | 0.000 |

*Table 11 MGA results based en hospital type*

# 5. Discussion, recommendations and conclusions

Dutch hospitals are ahead in digitization, a driver for the digital transformation that has accelerated due to Covid-19 (Taylor et al., 2021). In this light the use of department specific Lightweight IT (Bygstad & Øvrelid, 2020) and Big Data (Wang et al., 2018) is growing in healthcare environments. The capabilities to use these innovations should lead to a higher level of patient service performance (Wu & Hu, 2012). The understanding of these effects on department level from a healthcare point of view is still limited. This research aimed to address these specific gaps in the literature.

## 5.1. Theoretical contribution

This study designed and tested a research model that states that on hospital department level, the deployment of lighweight IT by the use of Modular Lighweight Clinical Systems (MLCS) and the use of Big Data Analytics Capabilities (BDAC) can increase the patient service performance by simultaneously make use of exploitative and explorative innovation. The results of this study provide partial evidence for this statement. On the one hand, we find evidence that there is indeed a significant relationship between the BDAC and the innovation ambidexterity (IA) of a hospital department. This supports the theory that the use of BDAC contributes positively via dynamic capabilities to the innovation capacity of an organization (Mikalef et al., 2019). In addition, we also see the positive contribution of IA on Patient Service Performance (Jansen et al., 2006), in particular by the ability to make use of BDAC (Wang et al., 2019). This research adds to the body of knowledge that these effects are significant on a hospital department level in Dutch hospitals.

On the other hand, this study shows that the predicted positive relationship between MLCS and IA (Bygstad & Øvrelid, 2020) cannot be found at hospital department level, in contrast to previous research, which showed this at the organizational level. Further analysis has shown that the missing effect of MLCS on IA can be partly explained by the strong relationship between BDAC and IA. Without the effect of BDAC on IA, there is a positive effect of MLCS on IA. This suggests that there is a relationship between MLCS and BDAC. From the theory we see that the use of MLCS in the form of sensors and remote monitors generates a lot of data (Wang et al., 2018), which calls for the deployment of BDAC (Wang et al., 2019).

Another possible explanation for the missing effect of MLCS on IA could be that there are still limited scientific articles for the use of MLCS in hospitals since MLCS is a newer phenomenon in hospitals than BDA, which has been around for longer from the perspective of Business Intelligence (Božič & Dimovski, 2019). Hospitals are generally more conservative in using new techniques. As BDAC may have been adopted for longer and more, MLCS, on the other hand, is even newer and may need more proof.

## 5.2. Recommendations for practice

Hospitals have a central interest and that is the interest of the patient. To work on increasing the Service Performance for this patient, hospitals will have to innovate at department level. And in an explorative as well as an exploitative way. As far as the deployment of MLCS is concerned, this use of wearable sensors, remote monitoring and use of patient apps will only increase in the coming years. Partly due to the fact that hospitals have to work even more efficiently and costs have to be limited. Due to the use of MLCS, patients can be monitored much more remotely and will ultimately be much less likely to visit hospitals and, through the use of apps, they will be able to keep control much more in their own hands.

By using MLCS, among other things, a lot of data will be generated from which hospitals can derive a lot of value, which will ultimately benefit the patient. If we consider this from a BDAC perspective, hospitals will have to focus on capabilities to use the available Big Data for decision making and insight, both at management level and at patient level. In addition, new capacities need to be developed in order to be able to take the next step in the future of Big Data.

## 5.3. Limitations and recommendations for further research

There are several limitations regarding this research. These limitations can be a starting point for future research. In this study, the assumed relationship between MLCS and IA has not been demonstrated. This was mainly due to the influence of BDAC on IA. Further research into this phenomenon is necessary, whereby possible other influences as mediating or moderating factors on the assumed relationship that have not been included in this study can be examined. In general more research is needed on the use of MLCS in hospital wards. Not only because of the unproven relationship between MLCS and IA, but because of the fact that we see its use increasing.

There may still be a difference in the type of hospital, in particular the academic hospitals, in the use of MLCS and BDAC and the investigated relationship with IA and PSP. Within this study, the sample size for the academic hospitals was too small, so it could not be specifically investigated. Follow-up research could focus on these academic hospitals.

In addition, this research was conducted within Dutch hospital departments. Follow-up research could focus on European, American or non-Western hospitals to investigate whether these results are generalizable.

## 5.4. Conclusions

Hopefully, the results of this research will contribute to a better understanding of the usefulness and necessity of finding a balance between exploitative and exploratory innovation for hospitals in order to provide better care to patients. Especially considering the digital transformation that is currently in full swing in Dutch hospitals and which has been accelerated by the current Covid-19 situation. Hospitals can no longer ignore the use of patient apps and wearable sensors, because these days this is simply part of the daily life of the average patient. The enormous amounts of valuable data will have to be embraced by hospitals in order to be able to derive more added value from this that will benefit patient care.

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# Appendix 1 Invitation and Follow up messages (in Dutch)

**Social media messages:**

Initial:

Beste heer <naam>, of Beste mevrouw <naam>,

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

Follow-up

Beste heer <naam>, of Beste mevrouw <naam>,

Onlangs heeft u mijn connectieverzoek geaccepteerd. Voor mijn afstudeeronderzoek van de Master Business Process Management and IT onderzoek ik digitalisering binnen ziekenhuizen. Ik wil u vragen of u 15 minuten van uw kostbare tijd wil vrijmaken om deel te nemen aan een survey. De survey kunt u benaderen via https://lnkd.in/grvb94_i.  Mvg, Lars Jongen

**E-mail message internally within own hospital:**

Beste ,

Mijn naam is Lars Jongen en ik werk bij de afdeling ZIT. Momenteel volg ik de opleiding Business proces management and IT aan de Open Universiteit. Voor mijn afstudeeronderzoek doe ik onderzoek naar digitale transformatie binnen Nederlandse ziekenhuisafdelingen. Zou jij hiervoor een survey (anoniem) in willen vullen? Dit vraagt hoogstens 15 minuten van je tijd. De survey is te vinden op: https://limesurvey.ou.nl/index.php/766667?lang=nl.

Mocht de survey ook relevant zijn voor collega's of personen in je netwerk, dan zou ik je vriendelijk willen vragen om de survey te delen.
Mocht je vragen hebben, laat het dan gerust weten.
Bij voorbaat mijn hartelijke dank!

**Met vriendelijke groet,**

**Lars Jongen**

# Appendix 2 Survey (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:***

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

Dit zijn zowel nieuwe patiënten als herhaalbezoeken

***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?***

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

Indien u geen arts bent, kunt u in n.v.t. invullen

**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.

**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.

**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.

**Lightweight IT**

Lightweight IT betreft de flexibele hard- en software van ziekenhuizen die toegang biedt tot actuele (medische) gegevens en kan worden ingezet om werkprocessen te ondersteunen.

Lightweight IT-toepassingen betreffen goedkope en beschikbare technologie, bijvoorbeeld middelen zoals tablets, apps, sensoren, smartphones en smartboards. Medische professionals kunnen hiermee te allen tijde toegang verkrijgen tot op maat gemaakte medische gegevens, die opgehaald worden uit systemen met klinische data (bijvoorbeeld elektronisch patiëntendossier (EPD)). Deze vorm van IT ondersteunt in de voorziening van de directe informatiebehoefte van medische professionals, zoals bijvoorbeeld sensortechnologieën die de vitale functies van een patiënt helpen monitoren.

Onze Lightweight IT-toepassingen:

Kies het toepasselijke antwoord voor elk onderdeel:

helemaal oneens – oneens - enigszins oneens – neutraal - enigszins eens – eens - helemaal mee eens

- … worden snel toegevoegd op basis van verzoeken van onze medische professionals (medisch-, geneeskundig- en arts-specialisten).
- … bieden via gebruikersomgevingen (bijvoorbeeld (mobiele) applicaties) transparante toegang tot andere platformen en ziekenhuis-brede applicaties.
- … kunnen eenvoudig worden gereproduceerd door andere afdelingen.
- … zijn interactief, schaalbaar en configureerbaar.
- … versterken het overzicht in en transparantie van onze medische informatie, onafhankelijk van de functie van een medisch professional.
- … en ziekenhuis-brede systemen maken gebruik van en delen gestandaardiseerde data
- Onze Lightweight IT en elektronisch patiëntendossier (EPD) werken goed samen.
- De wijze waarop onze Lightweight IT-toepassingen zijn georganiseerd en geïntegreerd, maakt het mogelijk om snel veranderingen door te voeren in onze werkprocessen.

# Appendix 3 Step-by-step construction of data file

**Extracting the data from Limesurvey**

This appendix describes all steps from exporting the RAW data file from Limesurvey to obtaining the data file that is used for analysis in SmartPLS.

For extracting the data from Limesurvey, the settings are used according to the picture below.

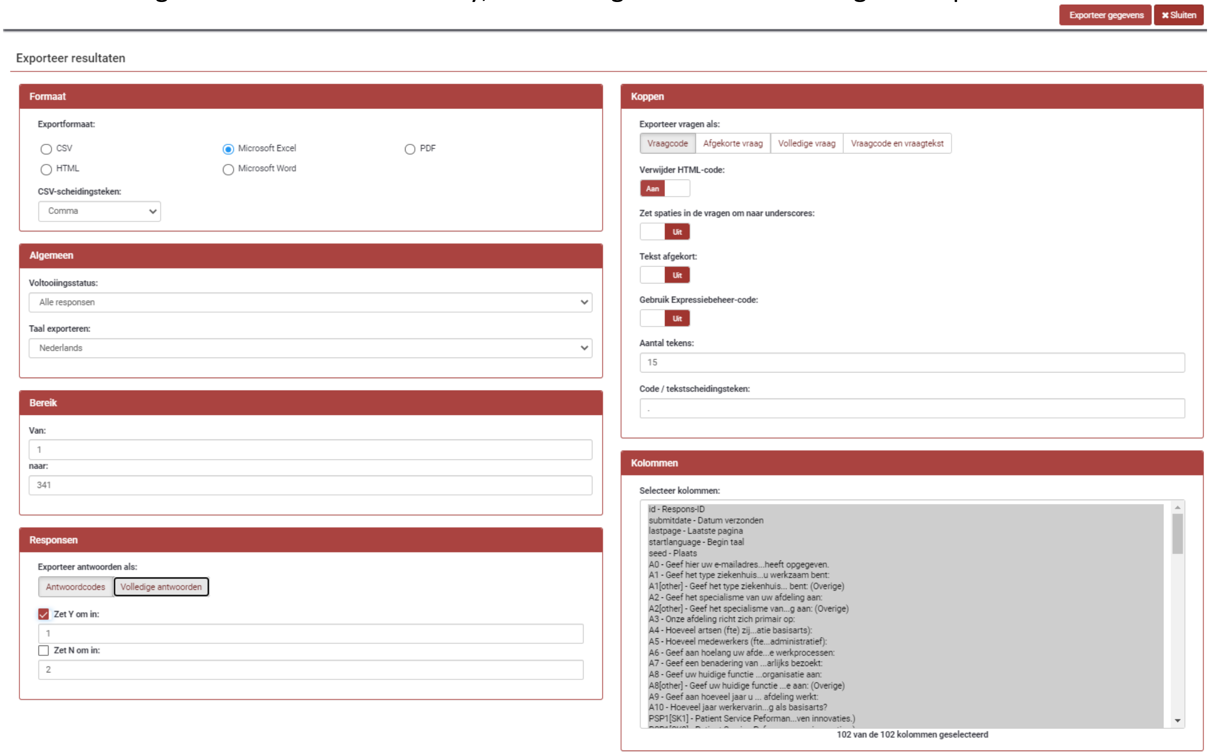


*Figure 6 Export settings data file in Limesurvey*

This led to an excel file with all data from 334 respondents.

**Cleaning up the RAW data file**

In Excel, all unnecessary columns that are not relevant to the research have been removed first. These are the following columns: id, submitdate, lastpage, startlanguage, seed, A0 (mailadress), Interviewtime, groupTime5293, A0Time, groupTime5289, A1Time, A2Time, A3Time, A4Time, A5Time, A6Time, A7Time, A8Time, A9Time, A10Time, groupTime5292, PSP1Time, OP1Time, groupTime5291, IV1Time, PA1Time, EBDMC1Time, groupTime5290, BDAC1Time, LIT1Time, AI1Time.

For columns A1 to A3 and A6 to A10, translation tables have been prepared and applied to convert the text fields into numerical values for further processing in SmartPLS. A4 and A5 are already numerical values. The translation tables are shown in on the next page.

| Full answers | Answercodes | Translated numerical code |
|---|---|---|
| **A1** | | |
| Universitair Medisch Centrum (UMC) | A1 | 1 |
| Samenwerkend Topklinisch opleidingsziekenhuis (STZ) | A2 | 2 |
| Samenwerkend Algemeen Ziekenhuis (SAZ) | A3 | 3 |
| Overig Algemeen Ziekenhuis (OAZ) | A4 | 4 |
| Overige | -oth- | 5 |
| | | |
| **A1[other]** | | |
| Huisartsenpraktijk | | 1 |
| MMC | | 2 |
| oncologisch centrum | | 3 |
| | | |
| **A2** | | |
| Anesthesiologie | A2 | 1 |
| Apotheek | A3 | 2 |
| Cardiologie | A4 | 3 |
| Cardiothoracale Chirurgie | A5 | 4 |
| Chirurgie | A6 | 5 |
| Dermatologie | A7 | 6 |
| Endocrinologie | A8 | 7 |
| Geriatrie | A9 | 8 |
| Hematologie | A16 | 9 |
| Immunologie | A15 | 10 |
| Infectieziekten | A10 | 11 |
| Intensive Care Volwassenen | A11 | 12 |
| Intensive Care Kinderen | A35 | 13 |
| Inwendige Geneeskunde | A1 | 14 |
| Keel-, neus- en oorziekten | A12 | 15 |
| Kindergeneeskunde | A13 | 16 |
| Neonatologie | A14 | 17 |
| Longziekten | A18 | 18 |
| Maag-, darm en leverziekten | A19 | 19 |
| Medische psychologie | A20 | 20 |
| Mondziekten-kaakchirurgie/Ziekenhuistandheelkunde | A21 | 21 |
| Neurochirurgie | A22 | 22 |
| Neurologie | A23 | 23 |
| Nierziekten | A24 | 24 |
| Oncologie | A17 | 25 |
| Oogheelkunde | A25 | 26 |
| Orthopedie | A26 | 27 |
| Plastische en Reconstructieve chirurgie | A27 | 28 |
| Psychiatrie | A28 | 29 |
| Reumatologie | A36 | 30 |
| Revalidatie | A29 | 31 |
| Spoedeisende hulp | A30 | 32 |
| Sportgeneeskunde | A31 | 33 |
| Urologie | A32 | 34 |
| Vasculaire geneeskunde | A33 | 35 |
| Verloskunde/Gynaecologie | A34 | 36 |

| | | |
|---|---|---|
| Overige | -oth- | 37 |
| | | |
| **A2[other]** | | |
| Operatie kamers en Dagbehandeling | | 1 |
| Huisartsgeneeskunde | | 2 |
| staf poliklinieken | | 3 |
| poli management | | 4 |
| management | | 5 |
| dietetiek, maatschappelijk werk , geestelijke verzorging en medische psychologie | | 6 |
| HRM, waar jullie afd zetten heb ik geantwoord vanuit de organisatie. Wat ik mis zijn vragen over het adaptievermogen van onze artsen en medewerkers. Hier wordt mijn inziens onvoldoende aandacht aan besteed. | | 7 |
| Raad van bestuur | | 8 |
| Chronische zorg | | 9 |
| Radiologie | | 10 |
| OK | | 11 |
| Klinische Fysica | | 12 |
| Radiotherapie | | 13 |
| Bloedafname laboratorium | | 14 |
| | | |
| **A3** | | |
| Verzekerbare zorg | A1 | 1 |
| Niet-verzekerbare zorg | A2 | 2 |
| Allebei (ongeveer evenveel) | A3 | 3 |
| | | |
| **A6** | | |
| 0-5 jaar | A1 | 1 |
| 6-10 jaar | A2 | 2 |
| 11-15 jaar | A3 | 3 |
| 16-20 jaar | A4 | 4 |
| 21-25 jaar | A5 | 5 |
| 25+ jaar | A6 | 6 |
| | | |
| **A7** | | |
| < 4.000 | A1 | 1 |
| 4.000 – 6.500 | A2 | 2 |
| 6.501 – 9.000 | A3 | 3 |
| 9.001 – 11.500 | A4 | 4 |
| 11.501 – 14.000 | A5 | 5 |
| > 14000 | A6 | 6 |
| | | |
| **A8** | | |
| Afdelingshoofd | A1 | 1 |
| Teamleider | A2 | 2 |
| Manager bedrijfsvoering | A3 | 3 |
| Verpleegkundig specialist | A4 | 4 |
| Physician assistant | A5 | 5 |
| Chef de Clinique | A6 | 6 |
| Arts (Specialist) | A7 | 7 |
| AIOS | A8 | 8 |
| ANIOS | A9 | 9 |

| | | |
|---|---|---|
| Overige | A10 | 10 |
| | | |
| **A8[other]** | | |
| Ziekenhuisapotheker, CPIO | | 1 |
| it | | 2 |
| adviseur digitale dienstverlening | | 3 |
| programma manager | | 4 |
| verpleegkundige | | 5 |
| RvB | | 6 |
| Medisch Specialist en CMIO | | 7 |
| Projectleider SPO en duurzame inzetbaarheid | | 8 |
| Gz psycholoog | | 9 |
| Orthoptist | | 10 |
| Doktersassistent | | 11 |
| Verpleegkundig endoscopist | | 12 |
| Anesthesie medewerker en gespec verpleegkundige | | 13 |
| GIOS | | 14 |
| Gz-psycholoog | | 15 |
| Radiotherapeutisch Laborant( MBB-er) | | 16 |
| specialist opleider bestuur | | 17 |
| | | |
| **A9** | | |
| 0–5 jaar | A1 | 1 |
| 6–10 jaar | A2 | 2 |
| 11–15 jaar | A3 | 3 |
| 16–20 jaar | A4 | 4 |
| 21–25 jaar | A5 | 5 |
| 25+ jaar | A6 | 6 |
| | | |
| **A10** | | |
| 0–5 jaar | A1 | 1 |
| 6–10 jaar | A2 | 2 |
| 11–15 jaar | A3 | 3 |
| 16–20 jaar | A4 | 4 |
| 21–25 jaar | A5 | 5 |
| 25+ jaar | A6 | 6 |
| n.v.t. | A7 | 7 |

*Table 12 Translation table survey data*

Of the partially completed surveys, it was checked whether there are records with less than 10% missing values, so that they can be added to the data to be used by supplementing them with average values. However, there were no surveys that met this criterion. As a result, only the 112 fully completed surveys remained. The content of these 112 surveys was further checked to the extent that it can be traced back to whether the basic principles of department level and department with patient contact have been met. As a result, four more were dropped (Board of Directors, HRM, Clinical Physics). To create a data file in which all data fields are filled, the empty fields of column A1[other], A2[other] and A8[other] are filled with the value 0. Here 0 corresponds to non-other. The missing values in column A10 are filled with the value 99. This value is completely outside the range of entered values to clearly see that this field is not filled in. This ultimately led to a fully filled data file consisting of 108 usable surveys.