Universiteit Leiden

ICT in Business and the Public Sector

Insights-Driven Enterprises: Characterization and analysis of the link between BI&A capacity and innovation capacity

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MASTER'S THESIS

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Insights-Driven Enterprises: Characterization and analysis of the link between BI&A capacity and innovation capacity

A Thesis Presented

by

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Submitted to Leiden University in partial fulfillment
of the requirements for the degree of

MASTER OF SCIENCE

July 2021

ICT in Business and the Public Sector

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ACKNOWLEDGMENTS

Throughout the last six months, I have received a great deal of support and assistance from professional and personal contacts. I would like to thank my first supervisor, Professor Stefan Pickl, whose academic expertise was invaluable in formulating the objectives and research questions. Your insightful feedback around business intelligence and analytics in the wider field of management science pushed me to sharpen the structure of my approach and brought my work to a higher level. I would also like to thank my second supervisor, Professor Wolfgang Bein, for his professional support from abroad.

In addition, I would like to thank my parents and brother for their wise guidance and understanding ear. You are always there for me. Finally, I could not have completed this thesis without the moral support of my friends at Leiden University and back at home. You have provided me with thought-provoking discussions as well as joyful distractions in these difficult months that were centered around the COVID-19 pandemic and the accompanying restrictions. I am looking forward to celebrating life with you soon again!

ABSTRACT

Insights-Driven Enterprises: Characterization and analysis of the link between BI&A capacity and innovation capacity

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To remain competitive and survive in dynamic market environments, firms are required to adapt flexibly to changing customer demands such as lower costs or increased personalization. It is widely recognized that the capacity to continuously deliver innovative outputs such as product, service, or process innovations strengthens a firm's competitive advantage. At the same time there are strong claims that business intelligence and analytics (BI&A) can support such innovation efforts. However, there is lack of theoretical understanding and empirical evidence linking a firm's BI&A capacity to its innovation capacity. In this study, we characterize and analyze the relationship between BI&A capacity and innovation capacity (RQ1) and between analytics maturity and BI&A capacity (RQ2) by relying on the dynamic capabilities perspective. We evaluate our model using data collected from 70 companies, applying partial least squares structural equation modelling. The results support the notion that a firm's BI&A capacity leads to an increased innovation capacity, which in turn enhances its competitive advantage. The theorized impact of the achieved analytics maturity stage on a firm's BI&A capacity however was found to be insignificant in this study. Nonetheless, the findings stress the importance of investing into BI&A in order to develop dynamic capabilities that allow a firm to sense environmental changes, transform data into knowledge, and use it to drive business decisions. Based on the answers to the two research questions, insights-driven enterprises can expect to be more innovative and competitive in dynamic market environments.

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LIST OF ABBREVIATIONS

Abbreviation	Explanation
AI	Artificial Intelligence
AM	Analytics Maturity
AVE	Average Variance Extracted
BA	Business Analytics
BI	Business Intelligence
BI&A	Business Intelligence and Analytics
BIACAP	BI&A Capacity
COM	Commercialization
DCP	Dynamic Capabilities Perspective
DSS	Decision Support System
DW	Data Warehousing
EIS	Executive Information System
HICSS	Hawaii International Conference on Systems Sciences
HTMT	Heterotrait-Monotrait
IDM	Idea Management
INVCAP	Innovation Capacity
IoT	Internet of Things
KTM	Knowledge and Technology Management
ML	Machine Learning
OLAP	Online Analytical Processing
PDV	Project Development
PLS	Partial Least Squares
RBV	Resource-Based View
RDBMS	Relational Database Management Systems
SEM	Structural Equation Modelling
STD	Sense-Transform-Drive

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CHAPTER 1

INTRODUCTION

1.1 Problem Statement: Managerial Decision Making

Situation

In recent years, both companies and end consumers generate an ever-increasing amount of data as a result of the digital revolution. It is predicted that the Global Datasphere, the summation of all data created around the world, will grow 430% from 2018 to 2025, reaching 175 Zettabytes (10^{21} bytes) (Reinsel et al., 2018). This amount of data on its own however does not provide business value, but instead actually poses challenges for companies to deal with. Many organizations have therefore introduced business intelligence and analytics (BI&A) to analyze this vast amount of data and as a means to improve managerial decision making.

The advances in BI&A development have provided unprecedented opportunities for organizations to derive insights, e.g., around product and service innovations from data (Duan et al., 2020). By analyzing both internal and external customer and consumer data, companies now have the chance to predict product and service features customers expect to see in the future (Božič & Dimovski, 2019b). These insights can support managerial decision making around product and service innovations (Aas & Breunig, 2017). Herewith, companies plan to provide better and faster responses to changing customer demands like increased personalization or cost awareness. This is crucial in today's fast-paced globalized world for companies to ultimately improve their competitive advantage.

Challenges: Developments in the Field of BI&A

However, while the developments in the field of business intelligence and analytics have made up the largest share of global business investment in information technology in recent years (Ransbotham & Kiron, 2017), not all BI&A initiatives live up to corporate's expectations. An estimated 70-80% of such projects fail to develop an organization-wide BI&A capacity that delivers actual business value (Gartner Inc., 2018). BI&A capacity is thereby defined as the firm's ability to sense environmental changes, transform new knowledge into an appropriate action mode, and enhance organizational decision making (Y. Chen & Lin, 2021). Studies found that reasons for BI&A project failures are manifold and range from poor data integration, undefined project scopes, lack of management support to missing in-house skills (Reggio & Astesiano, 2020).

BI&A can be implemented in various forms of complexity and to different degrees within firms, leading to classifications into different analytics maturity stages. Not all firms implementing BI&A necessarily achieve a high analytics maturity stage, as a recent Gartner study has found. Indeed, 87% of participating companies were found to only achieve a low analytics maturity stage (Gartner Inc., 2018). Such organizations exhibit specific characteristics such as BI&A functionality mainly based on reporting with a focus on hindsight, personal data extracts, and spreadsheet-based analyses (Gartner Inc., 2018; Król & Zdonek, 2020). These scientific findings may suggest that low analytics maturity is another impediment in developing a BI&A capacity that actually creates business value, which will be evaluated as part of this thesis.

Developing a High Analytics Maturity

The challenges in developing a high analytics maturity that contributes to the organization-wide BI&A capacity can explain why only few organizations were able to improve performance-related metrics through BI&A initiatives. For example, some recent studies considered profitability as a measure of performance and reported that only certain organizations were able to improve their profitability through BI&A (Hou, 2012; Mikalef et al., 2018; Torres et al., 2018). Further studies considered competitiveness as a measure of performance and found that some companies even experienced reduced competitiveness from their BI&A utility (Davenport, 2010; Gerbert et al., 2018).

Possible Solution: Innovation Capacity

The concept of innovation is already widely recognized as an important source for the competitiveness of companies (Crossan & Apaydin, 2010; Francis & Bessant, 2005). In order to deliver innovative outputs, such as radical product or service innovations, organizations need to have the capacity to continuously innovate. This organization's innovation capacity is defined as the potential to generate and deliver innovative outputs (Doroodian et al., 2014). This specific concept of innovation has been proven to lead to an increase in competitive advantages in dynamic market environments (Cooper, 1998; Doroodian et al., 2014; Evangelista & Vezzani, 2010; Rohrbeck & Gemünden, 2011; Saunila & Ukko, 2012). Yet, the question about which factors determine a firm's capacity to continuously innovate remains insufficiently researched (Neely & Hii, 2014). In the past, most studies only focused on "innovation inputs and outputs in terms of cost, speed to market, and numbers of new products" (Doroodian et al., 2014) to measure an organization’s innovation capacity, but they neglected the activities linking the inputs and outputs, also referred to as innovation practices (Rejeb et al., 2008).

Research Motivation

It remains unclear if BI&A capacity actually leads to competitive advantages and through which mechanism. At the same time, a majority of previous studies found both BI&A and innovation separately to be positively linked to different measures of firm performance and competitive advantages (e.g., Işik et al., 2013; Pitt et al., 2006; Rejeb et al., 2008; Torres et al., 2018). In addition, there are strong claims that BI&A can lead to product and service differentiation (e.g., Duan et al., 2020) and thereby contribute to an organization’s innovation capacity. Based on these findings we hypothesize that BI&A capacity leads to competitive advantages through the improvement of an organization’s innovation capacity.

While the link between innovation capacity and competitive advantage is proven, this thesis investigates if BI&A capacity actually leads to an increased innovation capacity. And although BI&A is increasingly used in organizations, only few studies have explored how it contributes to a firm’s capacity to innovate, specifically considering their innovation practices. Moreover, the influence of the achieved analytics maturity stage on the outcome of BI&A capacity, such as an increase in innovation capacity, has not been considered yet in conceptual models. This means there is lack of theory linking analytics maturity, BI&A capacity, and innovation capacity and hence also a lack of practical advice for practitioners and executives responsible for making decisions about BI&A investments in their companies.

1.2 Research Objective

Research Goals

This thesis aims to fill this research gap by suggesting and evaluating a new conceptual structural model to examine and characterize the relation between analytics maturity, BI&A capacity, and innovation capacity. Hereby, it aims to understand if, how and to what degree an organization's BI&A capacity contributes to its innovation capacity. In addition, the impact of analytics maturity on BI&A capacity is measured to consider the latest developments in the field BI&A.

From a practical perspective, the potential strategic value of BI&A as a source of innovation capacity and hence competitive advantage is evaluated. Increased awareness of such can potentially lead to stronger management support for BI&A initiatives, a lack of which was mentioned as a major reason for project failures.

Research Questions

Since the examination of the direct relation between BI&A capacity and innovation capacity poses a gap in academic research, this thesis tries to answer the following first research question:

RQ1: What is the effect of BI&A capacity on innovation capacity?

Since a low analytics maturity was identified as a potential impediment for generating value from BI&A initiatives, it is worth to be additionally considered as a variable in this research. In addition, analytics maturity has not been considered in previous academic research, i.e., in conceptual models. Therefore, this thesis tries to fill this gap by investigating the following second research question:

RQ2: What is the specific influence of analytics maturity on BI&A capacity?

1.3 Theoretical Research Framework

To link BI&A and innovation, the dynamic capabilities perspective (DCP) appears highly relevant, because both the BI&A capacity and innovation capacity constructs as introduced before are grounded in this theory. They are both consistent with the dynamic capabilities analysis model defined by Teece (2007) and Helfat and Peteraf (2009) since they both lead business firms to raise and improve organizational abilities to enhance their competitive advantages in a rapidly changing business environment.

Due to the ambiguity of the two concepts and respective measurement challenges, two existing academic models are utilized in this research. Specifically, the Sense-Transform-Drive (STD) conceptual model developed by Chen and Lin (2021) and their survey instrument is used to assess the endogenous variable BI&A capacity. In structural equation modelling (SEM) an endogenous variable is caused by one or more variables in the model but can also cause another endogenous variable in the model.

Next, the scale of measurement for the innovation capacity construct of Doroodian et al. (2014) is used to assess innovation capacity as the second endogenous variable of the structural model. In both models the researchers identified multiple underlying dynamic capabilities that make up their defined higher-order constructs. These capabilities manifest themselves with more generic dynamic capabilities such as creativity, absorption, and expansion. Specifically, absorption is related to an organization's ability to acknowledge the value of new information, assimilate it and commercialize it (W. M. Cohen & Levinthal, 1990). This is a central component of the path from utilizing BI&A to generating and delivering innovative outputs. Therefore, the dynamic capabilities perspective is used as a theoretical framework to examine the cause-effect relationship between the two constructs.

1.4 Organization of the Thesis

This thesis is structured in seven main chapters. The **first** one introduces the reader to the topic, states the research questions and emphasizes the purpose of this study. It further describes the organization of the thesis.

The **second** chapter consists of the literature review covering the developments in BI&A and links them to the concept of analytics maturity. In addition, the dynamic capabilities perspective is introduced as a theoretical framework to examine underlying BI&A and innovation capabilities of the two higher-order constructs.

In the **third** chapter, the conceptual research model is developed based on the previous findings and respective hypotheses are derived. Specifically, the relationships between analytics maturity, BI&A capacity, and innovation capacity are theorized.

The **fourth** chapter outlines the research model and defines the model constructs and measurement as well as the data analysis method. Here, the three main variables and additional control variables are outlined, and the partial least squares structural equation modelling approach introduced.

In the **fifth** chapter, the data analysis and results are described. After mentioning the descriptive statistics of the survey responses, a number of statistical measures are analyzed as part of the measurement model and structural model evaluation. The findings are then used to test the proposed hypotheses.

Chapter **six** concludes this thesis by outlining the theoretical key findings, their contribution to academic research, and managerial implications for businesses interested in BI&A. It further addresses limitations of the study and avenues for future research.

Finally, chapter **seven** states a brief conclusion of the overall thesis. Here, the link from the initially proposed research questions and hypotheses to the final results and their interpretations is drawn again to give a comprehensive overview of the thesis.

CHAPTER 2

LITERATURE REVIEW AND THEORETICAL DEDUCTION

2.1 Analysis of Relevant Literature

2.1.1 Development and Characterization of BI&A

Terminology

Although the term business intelligence (BI) has only gained popularity with the increasing amount of data generation in the last decade, the term first appeared in Deven's Cyclopædia of Commercial and Business Anecdotes (1865). He noted that the ability to retrieve information and react on it is fundamental to business intelligence (Devens, 1865). Almost one hundred years later, a researcher at IBM published an article in which he defines business intelligence as "the ability to apprehend the interrelationships of presented facts in such a way as to guide action towards a desired goal." (Luhn, 1958). In 1989, BI was then defined as an umbrella term for "concepts and methods to improve business decision making by using fact-based support systems" by Howard Dresner, later a Gartner Group analyst (Power, 2007). However, its usage was not widespread until the late 1990s (Power, 2007).

"The unprecedented interest in this discipline has also resulted in an ongoing 'conceptual confusion' in which many scholars and practitioners often misinterpret its foundational concepts or interpret them in mutually inconsistent ways." (Marjanovic & Dinter, 2018, p. 776). While some researchers use the terms BI and business analytics (BA) synonymously (B. Gupta et al., 2015), other scholars and practitioners use BI and BA to describe different elements of the broader field of analytics. For example, BI often refers to spreadsheet-based reporting or technical aspects such as databases, while BA is concerned with "advanced analytical tools, such as predictive analytics or data mining" (Marjanovic & Dinter, 2018, p. 776; see also Watson, 2014; Gupta et al., 2015).

Ever since its first appearance, numerous definitions of BI have been used in academic and practitioner literature and it is a research stream that can be considered as still in development (Ponelis & Britz, 2011). In this thesis, the umbrella term of business intelligence and analytics is adopted to support a comprehensive understanding of analytics. This holistic term "refer[s] to the techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand its business and market and make timely business decisions" (H. Chen et al., 2012, p. 1166). This theory-based definition is suggested to ensure a common understanding of the term throughout this thesis and it matches the definition used in Chen and Lin's (2021) model which is utilized to assess an organization's BI&A capacity as part of this research.

Historical Origin

BI&A research has its roots in the development of computer-based decision support systems (DSS) in the 1960s (Watson, 2009). Those then evolved to data warehousing (DW), executive information systems (EIS) and business intelligence in the late 1980s and early 1990s (Power, 2007). While Marjanovic and Dinter (2018) support Power's (2007) claim that BI originates from DSS, they argue that BI research still diverges from more traditional DSS research.

In their research, they analyzed the historical origins of business intelligence and analytics by identifying main research themes in the 28-year history of the Hawaii

International Conference on Systems Sciences (HICSS) longest-running minitrack on BI- and BA-related topics. Due to its good reputation and long history, HICSS publications are suitable to reflect and to learn about this evolution (H. Chen et al., 2012).

Group	Period	Focus	No. of papers
1	1990-1996	Executive information systems (EIS)	38
2	1997-2003	Data warehousing (DW)	29
3	2004-2011	DW extended with business intelligence (BI)	36
4	2012-2017	BI extended with business analytics (BA) (from 2012) and big data (from 2013)	41
Total:			**144**

Table 1: Grouping of HICSS BI&A minitrack papers
(Marjanovic & Dinter, 2018, p. 780)

The descriptive and lexical analyses of papers presented at HICSS BI&A minitrack confirm that the "evolving progress from EIS, DW, BI, BA, and, most recently, big data is fully aligned with industry trends" (Marjanovic & Dinter, 2018, p. 788).

The findings show that the first period (1990-1996) was less concerned with technology, but more with organizational features and use cases of EIS (Marjanovic & Dinter, 2018). In the second period (1997-2003), research had a strong focus on technical aspects of DW and key themes were performance-related issues, metrics, and metadata (Marjanovic & Dinter, 2018). Then, from 2004 on the focus laid on the challenges of turning data into information while technical aspects of databases and DW moved into the background (Marjanovic & Dinter, 2018). The identified key themes "value" and "knowledge" suggest that there were "challenges in deriving business value of BI technology and turning insights into knowledge" (Marjanovic & Dinter, 2018, p. 787). Since 2012, BI remained the key theme among the analyzed papers, however its interpretation became quite diverse, and one could notice a shift towards the increased mentioning of BA and the big data concept.

All identified key concepts and themes observed across the four different phases by Marjanovic and Dinter (2018) can be found in Table 1 in Appendix A. Similar to the phases and developments outlined above, Chen et al. (2012) and Davenport (2013) divide the evolution of BI&A into three major stages.

BI&A 1.0 (1970 – 2000)

The first evolutionary phase of BI&A starts in the early 1970s and focuses mainly on the extraction, transformation and loading process of structured data from transactional systems in order to convert them into the right format for statistical analyses (Chaudhuri et al., 2011; Eggert & Alberts, 2020; Turban et al., 2008; Watson & Wixom, 2007). The storing of collected data is typically done in relational database management systems (RDBMS) and data warehouses. Since the 1980s, data mining techniques and online analytical processing (OLAP) applications are additionally used for the data analysis and reports and dashboards are utilized more frequently (H. Chen et al., 2012; Davenport, 2013).

BI&A 2.0 (2000 – 2010)

In the early 2000s the rise of the internet acts a driver for the second evolutionary phase of BI&A (Eggert & Alberts, 2020). The increasing amount of unstructured, user-generated social media data, collected through Web 2.0 applications, opens opportunities to collect and analyze customer feedback but also requires new analytics capabilities. For example, “systems of BI&A 2.0 require mature text mining, web mining, and social network analysis capabilities” in order to process unstructured customer data (Eggert & Alberts, 2020, p. 688). This customer feedback and opinion data is increasingly used for user-centered advertisement by companies like Amazon, Google, and Facebook, thereby enabling new innovative business models (H. Chen et al., 2012; Davenport, 2013).

BI&A 3.0 (2010 – Present)

The next evolutionary phase BI&A 3.0 is driven by the rise of the Internet of Things (IoT) and focuses on the analysis of large quantities of unstructured data generated by mobile devices and IoT sensors (Davenport, 2013). These sensor-based devices, which are often equipped with radio-frequency identification tags, are connected to the internet and therefore enable "location-aware, person-centered, and context-relevant operations and transactions" (H. Chen et al., 2012, p. 1168). During this phase research has focused on the analysis of mobile phone data such as geographical position data collected by location-based services (Eggert & Alberts, 2020; Lehrer et al., 2011).

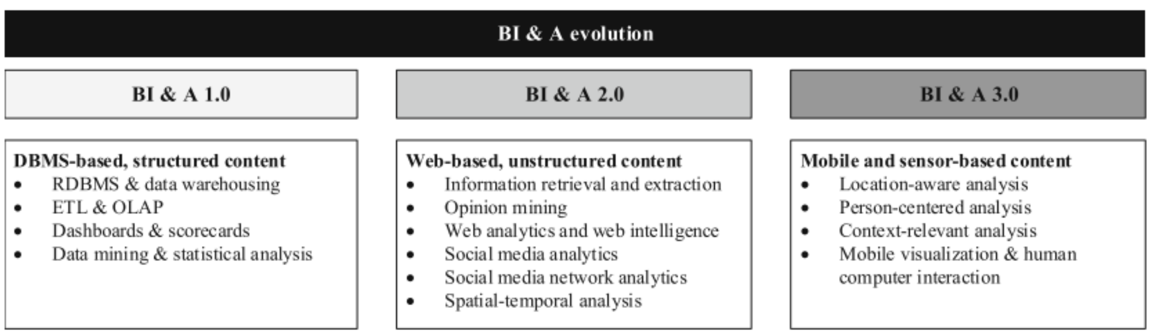

Figure 1: Characteristics of BI&A evolution
(Eggert & Alberts, 2020, p. 687)

Big Data Analytics (2013 – Present)

With the growing size, variety and number of available data sets collected by a number of different devices, the term big data has become more popular in academic research since 2013 (Marjanovic & Dinter, 2018) to describe this phenomenon. The qualities of big data are often represented by "volume", "variety", and "velocity", referring to the quantity, type and nature of the data as well as the speed at which it is generated (H.

Chen et al., 2012; Davenport, 2013). Companies such as Oracle, IBM and SASS and other researchers have labeled more V's to describe quantities of big data and current usage of the term also refers to certain advanced data analytics methods that extract value from it (e.g., Lee, 2017). Since big data (analytics) remains one of the most hyped, and one of the most vaguely defined business terms in use (Mullainathan, 2013), it will be regarded as a subcomponent of the introduced umbrella term BI&A.

Current BI&A Key Topics

A taxonomy-based literature review by Eggert and Alberts (2020) showed a clear trend towards BI&A 3.0 in academic papers, emphasizing a higher research interest. The number of retrieved articles related to the third evolutionary stage of BI&A increased from four in 2010 to 16 and 11 in 2017 and 2018 respectively (Eggert & Alberts, 2020). Based on their developed taxonomy, the researchers also identified key topics in each of the defined dimensions such as technologies, analysis techniques, analytics maturity, and emerging research area. The findings show that most information system research from 2010 to 2018 focused on data analytics techniques (52 hits), i.e., optimization techniques (28 hits), and addresses the descriptive (25 hits) or predictive analytics maturity level (18 hits) with "the emerging research areas, *network* and *mobile analytics* [receiving] the highest attention so far (25 and 26 hits)" (Eggert & Alberts, 2020, p. 701). The summarized results of the taxonomy-based literature review can be seen in Figure 12 in Appendix A.

The Gartner Hype Cycle for Analytics and Business Intelligence 2019 (see Figure 2) provides arguments to confirm this and shows trends that are on the rise. Topics such as business intelligence as a service, social analytics, predictive analytics, and visual data discovery have been identified as zero to five years close to reaching the plateau of productivity, as of July 2019 (Gartner Inc., 2019). On the other hand, currently hyped trends and innovations such as immersive analytics, continuous intelligence, graph analytics, or data lakes (repositories for large quantities of structured and unstructured data) are estimated to take another five to 10 years to reach maturity, as of 2019 (Gartner Inc., 2019).

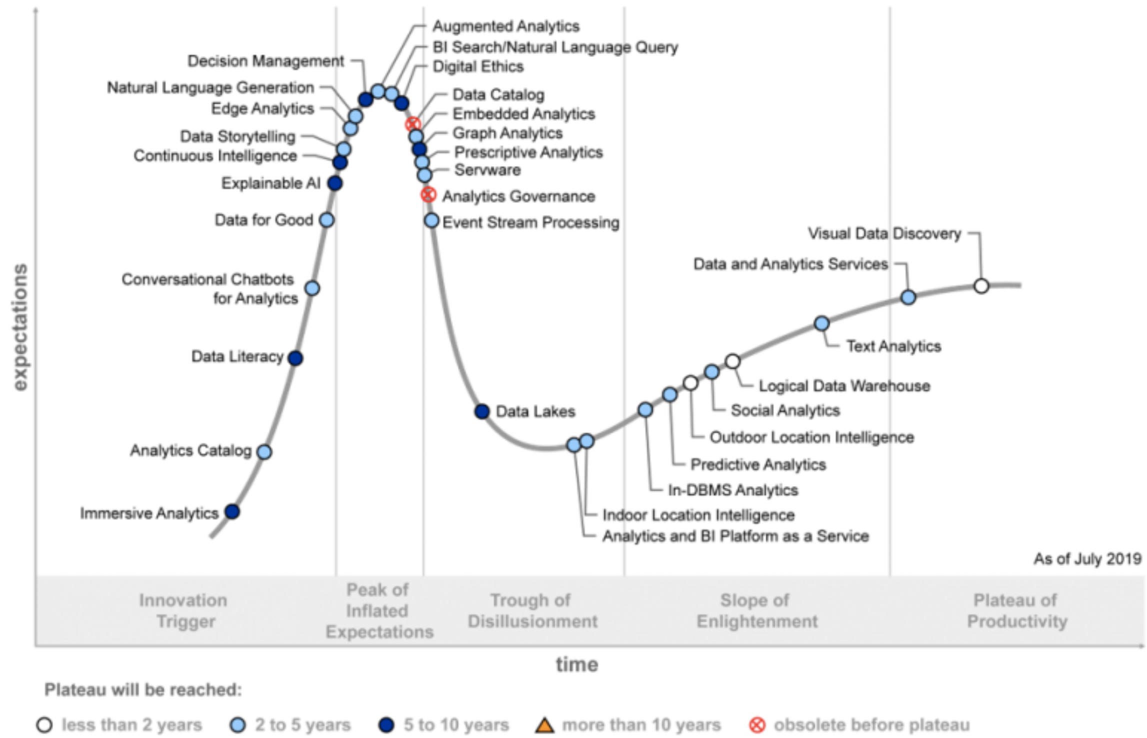

Figure 2: Gartner Hype Cycle for Analytics and Business Intelligence, 2019
(Gartner Inc., 2019)

The identified topics in the Gartner Hype Cycle are mostly consistent with the results from the taxonomy-based literature review by Eggert and Alberts (2020). Based on these findings, one can contend that BI&A is still in its third evolutionary wave in 2021, focusing mostly on the integration of unstructured data of a variety of mobile and sensor devices.

Summary of the Development and Characterization of BI&A

In summary, the identified phases show how with the advances in technology, the focus of analytics applications has also shifted over the years. Originally, the focus of BI&A applications was to present historical information in the form of structured data that allowed users to analyze it (Eckerson, 2003; Işik et al., 2013). Those results could then in turn support management in making more effective decisions (Eckerson, 2003; Işik et al., 2013). Modern BI&A systems now allow for the processing of real-time and unstructured data from both internal and external sources based on advanced information technology and methods (Davenport, 2010; Foley & Guillemette, 2010). These systems allow users to collect, store, analyze and convert data into insightful information or knowledge to provide intelligent solutions for organizational decision making (Božič & Dimovski, 2019a; H. Chen et al., 2012). These developments in the field of BI&A can be linked to analytics maturity stages which will be outlined in the following chapter.

2.1.2 Analytics Maturity

Definition

In general, the ability of an organization to continuously improve in a particular discipline can be defined and assessed as “maturity”. This very broad notion of “maturity” means as much as “fully developed” or “perfect” and can be measured through maturity models that assess a current state and provide orientation for improvement or indicate a path to perfection. While a broad number of maturity models exist, most of them qualitatively assess people and culture, processes and structures, or objects and technology (Mettler, 2011).

Analytics is regarded as a discipline whose maturity can be assessed through so-called analytics maturity models. These models provide a framework to examine and monitor the evolution of an organization's "ability to manage its internal and external data and use this data to inform business decisions" ("Analytics Maturity Models", 2020). This evolution is usually represented by a sequence of levels or stages that are outlined below. These models help organizations to assess how successfully they leverage their resources and capabilities to get value out of data ("Analytics Maturity Models", 2020). Herewith, they further assist to identify the effort required to complete and progress from a current maturity stage to the next one.

Analytic Maturity Stages

In a first-ever extensive literature review, Król & Zdonek (2020) have presented and summarized selected features of the eleven most popular organizations' analytics maturity models. Although each model uses different terms to describe different stages of analytics maturity, most of them are comprised of up to four different evolutionary stages that share similar characteristics. Presently, analytics maturity can be divided into the following four broader stages: (1) descriptive analytics, (2) diagnostic analytics, (3) predictive analytics, and (4) prescriptive analytics (Gartner Inc., 2019; Król & Zdonek, 2020).

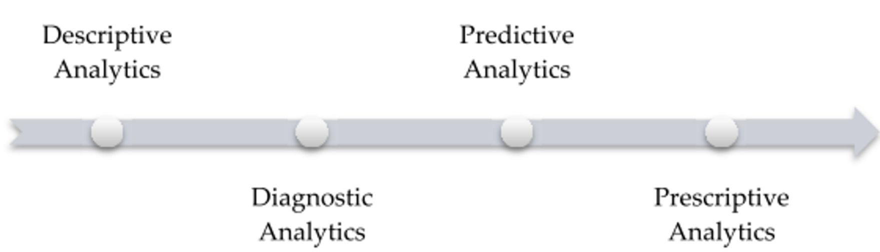

Figure 3: Analytics maturity path
(Modified from source: Król & Zdonek, 2020, p. 3)

In each stage, different analytical technologies and methods are utilized, that will be outlined further below. While the transition is very gradual in general, sometimes different teams or departments of the same company achieve a different level of analytics maturity. Furthermore, analytics maturity progression does not occur unidirectional only, e.g., if a company achieves the predictive analytics level, it does not abandon the previously established diagnostic analytic techniques ("Analytics Maturity Models", 2020). Instead, these four maturity stages co-exist and complement each other in analytics practice and will remain of utmost relevance in the next decades to come.

From descriptive to prescriptive analytics, these organizations' analytics maturity stages are placed on the analytics maturity path (see Figure 3). Generally, with an increasing maturity stage, organizations are able to make better decisions faster (Intel Corporation, 2017; Król & Zdonek, 2020). Also, "the extent to which forecasts and simulations are used increases" (Król & Zdonek, 2020, p. 4). The four maturity stages are characterized as follows.

Descriptive analytics is concerned with learning about and understanding reality by analyzing data and isolating the patterns it contains (hindsight – what happened, technologies: files, RDBMS, early data warehouse, OLAP) (Intel Corporation, 2017; Król & Zdonek, 2020). These patterns allow companies to answer the question "What happened?" (Król & Zdonek, 2020) and serve as a primary source of information for management, often in the form of dashboards or scorecards (Watson, 2014). Descriptive analytics explores, for example, the effectiveness of executed marketing activities or past customer shopping behavior.

Diagnostic analytics is often considered equivalent to traditional analytics, providing an answer to the question, "Why did it happen?" (insight – what happened and why, technologies: enterprise data warehouse, in-memory DBs and processing) (Intel Corporation, 2017; Król & Zdonek, 2020). Through the necessary process of data collection, systematization, analysis, and interpretation, there are delays in making decisions and consequently taking actions based on the analysis. By incorporating historical data, “diagnostic analytics enables the detection of regularities and quantitative relationships between variables” (Król & Zdonek, 2020, p. 3). Ultimately, management again makes the decision on how to interpret the information and to use it (Król & Zdonek, 2020).

Predictive Analytics analyzes current data in addition to historical data to model and create simulations and forecasts to find out what might happen in the future (foresight - what will happen, when, and why, technologies: No/NewSQL, mature in-memory DB and processing, early data lake) (Intel Corporation, 2017; Król & Zdonek, 2020). Thus, predictive analytics can be considered advanced analytics and can answer the question "What will happen in the future?" by predicting future events and trends (Król & Zdonek, 2020). For this purpose, patterns and relationships that occurred in the past are searched for and analyzed in order to use the resulting conclusions to make forecasts (Watson, 2014).

Prescriptive analytics complements predictive analytics by using simulations and machine learning (ML). These techniques propose actions that attain anticipated results if they are taken (simulation-driven analysis and decision-making, technology: mature data lake) (Intel Corporation, 2017; Król & Zdonek, 2020). Hereby, prescriptive analytics can answer the question "What actions should be taken?" and supports the decision-making process (Król & Zdonek, 2020; Watson, 2014).

For this purpose, real-time analytics are used to collect data and, above all, to "detect general regularities and patterns" (Król & Zdonek, 2020, p. 4). "On this basis, analytics models are created and then placed in the data stream." (Król & Zdonek, 2020, p. 4). By monitoring a customer's behavior patterns and interactions with a company, the model can suggest an optimal action at a given time (Król & Zdonek, 2020). "This is the so-called 'perishable insight' that can be discovered and used in action only in real time." (Król & Zdonek, 2020, p. 4). A common example are companies that sell "perishable" goods, e.g., airline seats, hotel rooms or rental cars (Watson, 2014).

Król and Zdonek (2020) further define more automated prescriptive analytics using artificial intelligence (AI) as **cognitive analytics** and consider it a fifth maturity stage. However, due to the similar nature, cognitive analytics will be counted towards prescriptive analytics in this thesis to describe advanced analytics using ML and AI in simulations to suggest optimal actions to be taken to achieve a desired output or goal (Król & Zdonek, 2020), regardless of the level of automation.

As mentioned before, these higher levels of analytics use AI techniques. Machine learning is a crucial supporting technology for AI and can be briefly described as "a computational method which allows machines to act or 'think' without being specifically programmed to perform specific actions." (Król & Zdonek, 2020, p. 4). These methods are built on algorithms that are able to "learn" from data and predict future outcomes (Król & Zdonek, 2020).

Summary of Analytics Maturity

Thus, and following the broader levels of maturity illustrated by Gartner in its annual BI magic quadrant review, the four distinct stages: (1) descriptive, (2) diagnostic, (3) predictive, and (4) prescriptive will be distinguished. The progression from descriptive to prescriptive analytics can also be expressed through the following questions: "What happened? Why did it happen? What will happen? How can we make it happen?" (Watson, 2014, p. 1251) and is represented in a number of analytics maturity models (Eckerson, 2004; Król & Zdonek, 2020).

Although it is termed as analytics maturity model, the model can be used to assess an organization's BI&A maturity because the four stages of analytics maturity outlined above impact all components of BI&A. For each stage, the applications, technical infrastructure, technologies, analysis methods (e.g., regression, factor, cluster, time series) and organizational elements (e.g., data governance, training, management) of BI&A are impacted. The four stages also represent a shift from simple analysis and reporting possibilities to more advanced analytics with a focus on foresight, the ability to predict what will happen or be needed in the future.

Based on this shift, we hypothesize that the results achieved with BI&A are likely to become more meaningful with an increasing maturity level. This hypothesis is related to the second research question (RQ2) of this thesis which is concerned with the specific influence of analytics maturity on a firm's BI&A capacity. It will be examined as part of the conceptual model outlined in the following chapters.

2.2 Theoretical Derivation of Conceptual Model

As part of this thesis, a conceptual model examining and characterizing the relation between BI&A capacity and innovation capacity is developed. The dynamic capabilities perspective was found most suitable as a theoretical framework to investigate this relation because both constructs are grounded in this theory. This approach builds on the well-known resource-based view (RBV) of the firm, which is outlined below, and is becoming increasingly popular in strategic management research (Tallman, 2006).

> "The point of taking a capabilities perspective is to examine closely the characteristics of the firm's internal assets, capabilities, and competencies and their impact on strategy and performance. The evidence is becoming clear that these, not market competition, are the determinants of sustained differences in performance levels from one firm to another." (Tallman, 2006, p. 2f.)

Since the conceptual model examines differences in performance level, i.e., in terms of an increase in innovation capacity, from one firm to another, the DCP is suitable as theoretical framework. Hence, in the next chapter the RBV and DCP are further outlined to build a common understanding as part of the theoretical derivation of the conceptual model. In a next step, BI&A and innovation are both examined from the dynamic capabilities perspective before deriving the conceptual model in this research.

2.2.1 Resource and Capability Perspectives

Resource-Based View

A popular strategic management perspective, the resource-based view of the firm, assumes that particular firm resources, competencies, and capabilities are required to remain competitive as a firm (J. B. Barney, 1991; Penrose, 1959; Peteraf, 1993; Spender, 1996; Wernerfelt, 1984). This perspective explains the differences in the performance of companies based on the creation, ownership, management and use of intangible assets, in particular knowledge and relationships. According to RBV, resources are only of value when a company uses and successfully deploys them in such a way that competitors cannot copy them. Hence, a key factor of competitive advantage is the firm's internal organization which "acts in conjunction with the external industry structure and positioning view of strategy" (Aas & Breunig, 2017; Porter, 1980, 1985).

Dynamic Capabilities Perspective

Teece et al. (1997) later coined the term dynamic capabilities perspective to extend the RBV theory to include external market variations. He states that "winners have been firms that can demonstrate timely responsiveness and rapid and flexible product innovation, coupled with the management capability to effectively coordinate and redeploy internal and external competences" (Teece et al., 1997, p. 517). Therefore, the dynamic capabilities perspective includes the notion of innovation and is not just inwardly focused on the organization and its strategies.

According to the dynamic capabilities perspective, an organization achieves sustainable performance by adapting to changing external environmental requirements. This is also referred to as evolutionary fitness, which is defined as "how well a dynamic capability enables an organization to make a living by creating, extending, or modifying its resource base" (Helfat et al., 2007, p. 120). "Because they build, integrate, and reconfigure other resources and ordinary capabilities" (Aas & Breunig, 2017), dynamic capabilities therefore involve adaptation and change by definition. In the context of other resources like financial assets or technology, a capability does however not represent a single resource. Instead, it is a distinctive and superior method of resource allocation (Aas & Breunig, 2017).

Summary of the Resource and Capabilities Perspectives

In conclusion, the resource-based view of strategic management has been extended by the dynamic capabilities perspective to include dynamic market environments (Eisenhardt & Martin, 2000). Accordingly, it is important that companies build new capabilities and create new knowledge to increase their innovative strength and competitiveness in dynamic market environments (W. M. Cohen & Levinthal, 1990; Kogut & Zander, 1993). The continuous adaptation of capabilities is imperative to remain competitive in the long term (Tallman, 2006). Dynamic capabilities avoid inflexibilities that generate inertia, inhibit development and suppress innovation, thus, creating a sustainable competitive advantage for firms (Leonard-Barton, 1992).

The DCP is a popular approach in strategic management and is increasingly used in academic research to investigate a wide range of dynamic capabilities, their relationships, and their effects. Hence, the underlying capabilities of BI&A capacity and innovation capacity are outlined in the following chapters.

2.2.2 BI&A Capacity and its underlying Capabilities

Previously Used Theoretical Frameworks

In the past, most studies have examined the impact of BI&A on organizations (Işik et al., 2013; D. Kiron et al., 2012; Torres & Sidorova, 2019) following the Information System Success Model by Petter et al. (2013) which is not able to explicitly determine the correlation between observed variables and performance increments (Burton-Jones & Gallivan, 2007). In two case studies, Işik et al. (2013) and Torres et al. (2018) used the information processing theory instead to examine the effect of business intelligence and analytics on firm performance. However, the theory could not generally interpret the relationship of BI&A and other influencing factors such as decision optimization, cognitive improvement, and environmental change, and ultimately, could not explain the impact of BI&A on the organization's internal mechanisms of performance (Y. Chen & Lin, 2021).

Commonly used in research on the value of IT investments (Drnevich & Croson, 2013), RBV is one of the few theories that explicitly considers firm performance as a dependent variable of BI&A (Elbashir et al., 2008, 2013). However, it is argued that the RBV is limited in its theoretical validity by the ambiguous representation of resources, capabilities, and firm evaluation, and has a tautology in the argument for corporate competitive advantage (Y. Chen & Lin, 2021; Priem & Butler, 2001).

More recent studies have therefore explored the role of analytics as micro-foundations of the dynamic capabilities perspective and accordingly considered the role of BI&A and related concepts as a single capability or technique, such as the Big Data Analytics Capability (Mikalef et al., 2020), the Big Data Decision-making Capability (Shamim et al., 2019), or the Operational Research technique (Conboy et al., 2020). However, Chen and Lin (2021) argue that these have not fully explored the complex capabilities of BI&A, specifically lacking an exploration of the complex systemic forces endogenous to BI&A in the perspective of the dynamic capabilities theory. Instead, they suggest a multi-dimensional model of BI&A made up of three underlying capabilities and thus do not regard BI&A as a single capability or technique.

Previously Identified BI&A Capabilities

In general, the dynamic capabilities perspective posits that BI&A is made up of one or multiple critical organizational capabilities that allow companies to identify threats and to capture opportunities (H. Chen et al., 2012; Sirmon et al., 2011). However, due to the application of numerous different theoretical perspectives, researchers have identified a broad variety of capabilities underlying BI&A in the past. The lack of uniform definitions of BI, BA, BI&A, BDA, etc. further contributes to this issue. And although more recent theoretical studies have adopted the dynamic capabilities perspective (e.g, Mikalef et al., 2020; Wamba et al., 2017), as of today no theoretical consensus about the underlying capabilities has been reached (Y. Chen & Lin, 2021). Table 2 provides a brief summary of capabilities examined in previous BI&A-related capability studies over the last decade.

Author(s)	**Identified BI&A Capabilities**
Kuilboer et al. (2010)	Organizational Memory, Information Integration, Insight Creation
Davenport and Patil (2012)	Management, Employees, Technology
Cosic et al. (2012)	Governance, Culture, Technology, People
Işik et al. (2013)	Data Quality, Integration with Other Systems, User Access, Flexibility, Management Support
Ramakrishnan et al. (2016)	BI Innovation-Infrastructure Capability, BI Process Capability, BI Integration Capability, BI Organizational Effectiveness
Gupta and George (2016)	Tangible Resources, Human Resources, Intangible Resources
Wamba et al. (2017)	Infrastructure flexibility, management and personnel expertise capabilities
Kulkarni et al. (2017)	Information Capability, BI System Capability
Karaboga (2019)	Technical Capability, Managerial Capability, Talent Capability
Mikalef et al. (2020)	Tangible, Human Skills, Intangible
Chen and Lin (2021)	Sensing, Transforming, Driving

Table 2: Summary of BI&A capabilities

The Sense-Transform-Drive (STD) BI&A Model

Based on the dynamic capabilities perspective, Chen and Lin (2021) conceptually developed the Sense-Transform-Drive model of BI to explore the core BI capabilities. Although, they refer to it as BI model, their definition of BI is equivalent to the introduced definition of BI&A in this thesis, and it is therefore referred to as BI&A model going forward. Herewith, they are the first to fully investigate the complex systemic forces that are endogenous to BI&A according to the DCP. In their study, they extracted the latent constructs and common attributes of BI&A through adoption of the co-citation context analysis approach and examined their internal correlations through a systematic review of relevant literature and empirical verification. In respect to the framework of strategic management, their developed STD conceptual model interprets the internal mechanics of BI&A as:

> "a system to **sense** (discern) environmental changes and **transform** new cognitive knowledge into an appropriate action mode to optimize business process and resource allocation, thus generating a systematic capacity to **drive** organizational decision making and enhance operating efficiency and effectiveness." (Y. Chen & Lin, 2021, p. 2)

STD Model Phases

These three important phases: (1) sense, (2) transform, and (3) drive, as indicated in the STD conceptual model (see Figure 4), represent three dynamic capabilities that combined generate an organization-wide BI&A capacity. The first dynamic capability "sense" enables companies to receive and discern timely and accurate relevant data (Y. Chen & Lin, 2021). The second dynamic capability "transform" then allows companies to analyze and transform this data into new knowledge for reaching consensus among stakeholders about resource reallocation or process re-engineering decisions (Y. Chen & Lin, 2021).

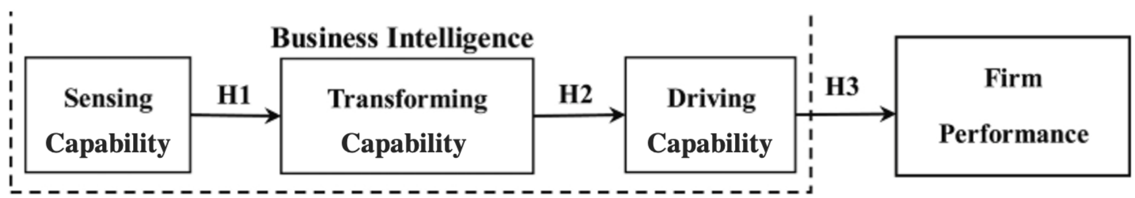

Figure 4: BI&A Sense-Transform-Drive (STD) Model
(Y. Chen & Lin, 2021, p. 6)

The third dynamic capability "drive" then enables companies to make these strategic and operating decisions that enable them to maintain and continuously create competitive advantages (Y. Chen & Lin, 2021).

Summary of BI&A Capacity

The STD BI&A model is in line with the dynamic capabilities perspective and suggests that an organization's BI&A capacity is made up of the three underlying dynamic capabilities: sense, transform, and drive. Thereby, allowing an organization to identify threats and to capture opportunities in the wider sense. Although, Chen and Lin (2021) investigated the effect of BI&A capacity on firm performance, this model remains valid to measure an organization's BI&A capacity as part of the conceptual model developed in this thesis. Their statistical results confirmed that the BI&A conceptual model is a composite system with interrelated capabilities that can be assessed through their developed survey instrument consisting of 19 indicators. Thus, and following the researchers' suggestion, this thesis abstracts a new latent construct at the higher-order level (i.e., BI&A capacity (BIACAP)), emphasizing a multi-dimensional understanding. The modified model can be seen in Figure 5 on the page.

In structural equation modelling, such a model is also referred to as measurement model because it allows researchers to measure the first- and second-order factors or latent constructs through the corresponding indicators. The $\beta_{1\text{-}9}$ values seen along the paths in the model in Figure 5 are however not path coefficients, but so-called outer loadings that determine an item's absolute contribution to its assigned latent factor or variable (Joseph F. Hair et al., 2017). The suggested BIACAP measurement model will be evaluated as part of the data analysis in Chapter 5 to verify whether this model is suitable to measure a firm's BI&A capacity.

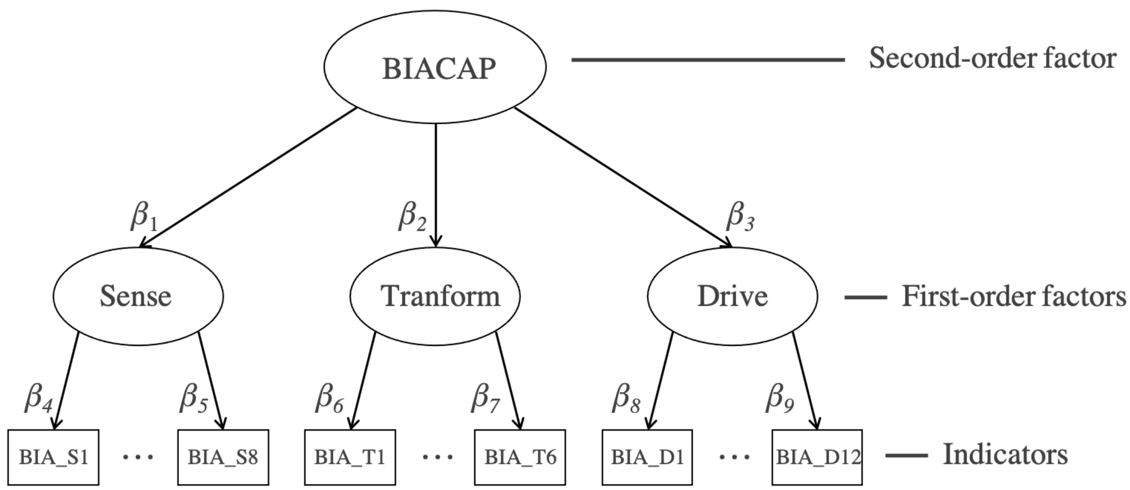

Figure 5: BI&A capacity (BIACAP) measurement model
(Modified from source: Y. Chen & Lin, 2021, p. 6)

Prior studies mostly examined the effect of BI&A on firm performance and came to different conclusions (e.g., Ashrafi et al., 2019; Y. Chen & Lin, 2021). At the same time there are "white paper" claims that BI&A helps firms to innovate, but so far there is little theoretical understanding or empirical evidence to support this. Therefore, this thesis attempts to fill this research gap by examining and characterizing the effect of a firm's BI&A capacity on its innovation capacity as defined in the following chapter (see also research motivation in Chapter 1.1).

2.2.3 Innovation Capacity and its underlying Capabilities

Importance of Innovation

The previous rules of competition have been changed by the globalization process and rapid technological change in recent decades, which has made innovation increasingly important for companies to stay competitive (Pitt et al., 2006; Rejeb et al., 2008). Market and cost advantages for a company today can be achieved particularly through innovations in the form of new or improved products and processes (Doroodian et al., 2014; OECD, 2005). The resulting product differentiation can further lead to increased demand, which ultimately boosts the company's performance (Doroodian et al., 2014; OECD, 2005).

"Innovation should be regarded as a sustainable and continuous process" (Doroodian et al., 2014, p. 1) and not just as the generation of new ideas or working methods (Sun et al., 2012). Accordingly, companies must commit to the permanent and continuous creation of innovation, as it is the key source for competitive advantage (Cooper, 1998). It is only through this "on-going and dynamic process of developing and improving new or existing products, processes, technologies capabilities, and management practices" (Doroodian et al., 2014, p. 1) that the continuous innovation creation becomes a reality for a company (Sun et al., 2012).

Definition of Innovation Capacity

Innovative organizations are characterized by their ability to properly manage creativity and capabilities such as the innovation capability (Saunila & Ukko, 2012). This capability can be comprehended as the organization's potential to innovate (Saunila & Ukko, 2012), or its "ability to continuously transform knowledge and ideas into new products, processes and systems for the benefit of the firm and its stakeholders" (Lerro et al., 2009, p. 11). This capability has been recognized as a higher-order capability because it has “the ability to mould and manage multiple capabilities” (Lawson & Samson, 2001, p. 380). Organizations in possess of this capability have “the ability to integrate key capabilities and resources of their firm to successfully stimulate innovation” (Lawson & Samson, 2001, p. 380).

The implementation and execution of innovation activities has already been positively linked to an organization’s future performance in empirical studies (e.g., Bowen et al., 2010; Rubera & Kirca, 2012). However, for the innovation activities to turn out successfully, different resources and capabilities are needed depending on the organization and industry (Aas & Breunig, 2017). The capacity to reproduce innovation success can be framed as the introduced innovation capability (Aas & Breunig, 2017) and its role be explored as micro-foundations of the DCP and accordingly be considered a single dynamic capability. However, it is also argued that “a firm’s capacity to innovate can be thought of as the potential of that firm to generate innovative output.” (Neely & Hii, 2014, p. 49). And an organization’s innovation capacity is dependent on corporate resources and underlying capabilities that enable it to explore and exploit opportunities (J. B. Barney, 1986; D. Teece & Pisano, 1994), emphasizing a multi-dimensional understanding of innovation capacity.

This innovation capacity is the more abstract potential of an organization to generative innovative outputs. On the other hand, individual innovations, e.g., new products or service innovations, are the outputs or results stemming from the innovation capacity. This thesis adopts the term innovation capacity and not innovation capability to emphasize a multi-dimensional understanding of the construct as outlined further below.

Difficulty of Measuring Innovation Capacity

Due to the dynamic nature of the innovation process, the valuation of an organization's innovation capacity is essential to ensure management support in further developing this capacity (Rejeb et al., 2008). While it is agreed that the "measurement of the innovation capacity is critical for both practitioners and academics" (Doroodian et al., 2014, p. 1), a variety of approaches, prescriptions, and practices can be found in the literature that can be confusing and contradictory (Adams et al., 2006). There are two main underlying reasons for this issue:

First, researchers have divided core innovation capabilities into different categories and viewed them in different contexts (e.g., den Hertog et al., 2010; Lawson & Samson, 2001; Terziovski, 2007) which has led to many diverse definitions of innovation capacity and related concepts such as innovation capability, innovation performance, or innovation that have been interchangeably used in the literature (Hogan et al., 2011). This has further caused confusion in defining and specifically measuring the concept. For example, Narcizo et al. (2017) revealed as many as 19 different definitions only of the term innovation capability and concluded that a unified definition is difficult to construct due to the variability in descriptions of the term.

Second, when measuring innovation capacity, most firms only consider innovation inputs and outputs measured by numbers of new products or patents, speed-to-market, and expenditure and neglect the processes in-between (Adams et al., 2006; Becheikh et al., 2006; Cordero, 1990). This implies, that the innovation process activities linking the inputs to the are not assessed (Rejeb et al., 2008), consequently a strong limitation exists in these approaches. In addition, due to the broad nature of the scope of innovative activities

(Rogers, 1998; Tohidi & Jabbari, 2011), adequate measurement of innovation capacity is likely to be difficult and previous proposed measurement scales and models have been limited (Calik et al., 2017).

Innovation Capacity Measurement Scale

Doroodian et al. (2014) generated a solution for the beforementioned confusion by developing a reliable and valid scale of measurement for the innovation capacity, which is defined as "a continuous improvement of the overall capability of firms to generate innovation" (Szeto, 2000. p. 150) in their research. This measurement scale for innovation capacity is specifically based on innovation activities and efforts rather than innovation process inputs or outputs. They used data collected from 175 SMEs to test its unidimensionality, reliability, and several components of validity. The results of these tests and additional exploratory and confirmatory factor analyses strongly support a four-dimensional scale for measuring innovation capacity (Doroodian et al., 2014). The identified dimensions of innovation capacity are knowledge and technology management (KTM), idea management (IDM), project development (PDV), and commercialization (COM) capabilities (Doroodian et al., 2014).

Based on the results of the exploratory factor analysis, the researchers consider the "innovation capacity (INVCAP) construct […] as a second-order latent factor measured by the four dimensions [mentioned above]" (Doroodian et al., 2014, p. 5). The related observed indicators, the so-called innovation practices, measure each of the four dimensions as first-order latent factors in turn. Their research model can be seen in Figure 6 on the next page.

Similar to the previously introduced BIACAP measurement model, also this measurement model will be evaluated as part of the data analysis in Chapter 5 to verify whether it is suitable to measure a firm's innovation capacity. Again, the β_{1-12} values along the paths in Figure 6 represent outer loadings in the context of a reflective measurement model in structural equation modelling. They are the estimated relationships between a latent variable and its related observed indicators.

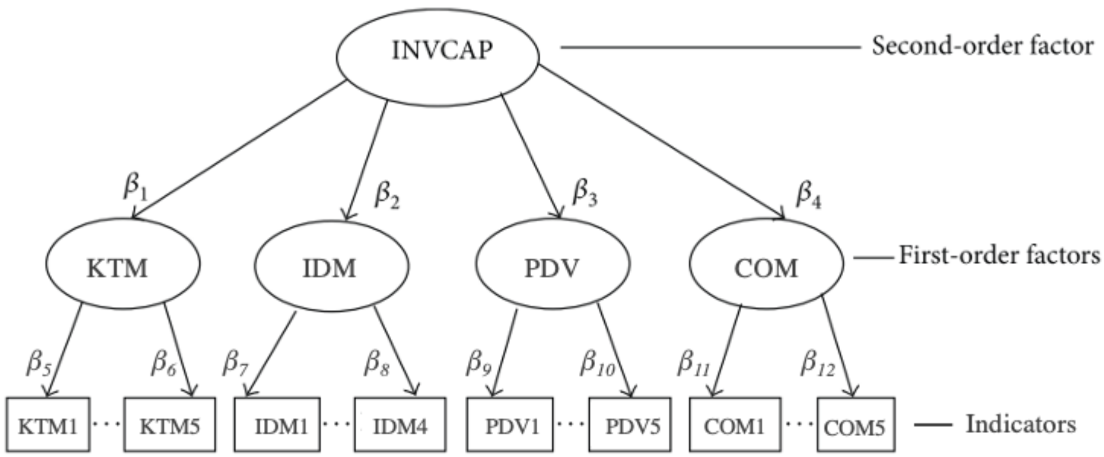

Figure 6: Innovation capacity (INVCAP) measurement model
(Modified from source: Doroodian et al., 2014, p. 5)

While innovations can occur in the form of "product, process, and organizational and marketing innovations", this model focuses on product, and process innovations as the main drivers for competitive advantage (Doroodian et al., 2014, p. 3; see also OECD, 2005)(Doroodian et al., 2014). Although not mentioned directly, service innovations are also counted towards product innovations and will therefore be mentioned explicitly going forward. In addition, the model includes both incremental improvements in existing products, services, and processes as well as producing fully new ones, referred to as radical changes (Doroodian et al., 2014). Herewith, the model covers all components of the definition for the technological product and process innovation (TPP) in the 3rd edition of Oslo Manual (OECD, 2005).

In their model, the idea management capability is defined as the ability to screen for and acquire innovative ideas, while the knowledge and technology management capability is defined as the "ability to assimilate, adapt to, and transform acquired knowledge and technology" (Doroodian et al., 2014, p. 9). On the other hand, the project development capability is defined as the ability to use high-tech tools and equipment for designing, engineering, prototyping, and testing, while the commercialization capability is defined as the ability to analyze markets and competitors and to commercialize innovations (Doroodian et al., 2014).

These definitions emphasize that those are dynamic capabilities grounded in the introduced DCP that allow a firm to alter its resource base by integrating, building, and reconfiguring competences. While the IDM and KTM capabilities relate to innovation discovery (ideation) in general, PDV and COM capabilities relate to innovation delivery (implementation) (Doroodian et al., 2014). The findings of the study show that these two nearly orthogonal dimensions: (1) discovery and (2) delivery are found to be the drivers for successful innovation (Doroodian et al., 2014). Those findings are in line with and further support previous work that came to the same conclusion about innovation drivers (Christensen & Raynor, 2003).

Summary of Innovation Capacity

The novelty of their research, strong research methodology and empirical verification provide a solid basis for an assessment of innovation capacity as outlined above. Thus, this thesis adopts the innovation capacity measurement model and the accompanying questionnaire scale developed by Doroodian et al. (2014). It will be the basis for the first research question RQ1 that is concerned with the effect of BI&A capacity on innovation capacity. The following chapter now introduces the statistical method used to link the two previously introduced measurement models, allowing us to examine the effect we are concerned with in RQ1.

2.3 Structural Equation Modelling

Structural equation modelling is a popular quantitative approach for observational and experimental research in a range of fields in sciences or business. It is often used to show the casual relationships between latent variables. For that matter it is composed of two components, the measurement model and the structural model as outlined below.

Measurement Model

The two previously introduced variables BI&A capacity (BIACAP) and innovation capacity (INVCAP) are latent constructs that cannot be measured directly. Instead, depending on the nature of the latent construct, it can either be represented (reflective) or constituted (formative) by its indicators. In a formative construct, the arrows are pointing from the indicators to the construct, indicating that the construct is fully composed by its indicators (Ringle et al., 2012). Hence, if one changed or removed an indicator, the meaning of the formative construct would change (Ringle et al., 2012). On the other hand, in a reflective construct, the measure indicators are caused by the construct. This is represented by arrows pointing from the reflective construct to the indicators, meaning the indicators are interchangeable (Joseph F. Hair et al., 2017).

This notion also applies for higher (or second)-order constructs that are more general concepts that are either reflective (represented) or formative (constituted) by its lower order constructs (Sarstedt et al., 2019). Again, the relation between higher and lower-order constructs “is not a question of causality, but rather a question of the nature of the hierarchical latent variable, as the higher-order construct (the general concept) does not exist without its lower-order constructs (dimensions).” (Becker et al., 2012, p. 362).

In our case, both BI&A capacity and innovation capacity are measured as reflective-reflective second-order constructs. In structural equation modelling they are referred to as measurement models (outer models) and they show the relationships between both directly measured variables and latent variables. These relationships are called outer loadings as briefly introduced in the corresponding chapters before.

Structural Model

In this thesis both research questions are concerned with the effect of one latent variable on another latent variable. Structural equation modelling allows us to show and examine these causal relationships between such variables. This part of SEM is referred to as structural model (inner model) and it only contains the latent variables and the relationships between them (Joseph F. Hair et al., 2017). These paths represent the hypotheses or the theoretical element of a research model (Joseph F. Hair et al., 2017). This also explains why structural equation modelling is sometimes also referred to as path analysis and the corresponding model called a path model. The path coefficients between two latent variables are then interpreted like standardized regression coefficients, meaning if BIACAP changes by one standard deviation, INVCAP changes by β standard deviations (with β being the path coefficient). The additional criteria for evaluating the structural model will be outlined in the data analysis in Chapter 6. One can further note that the terms latent variable, construct or factor can be used interchangeably. A general visual representation of the relationship between measurement model and structural model can be seen in Figure 7 below.

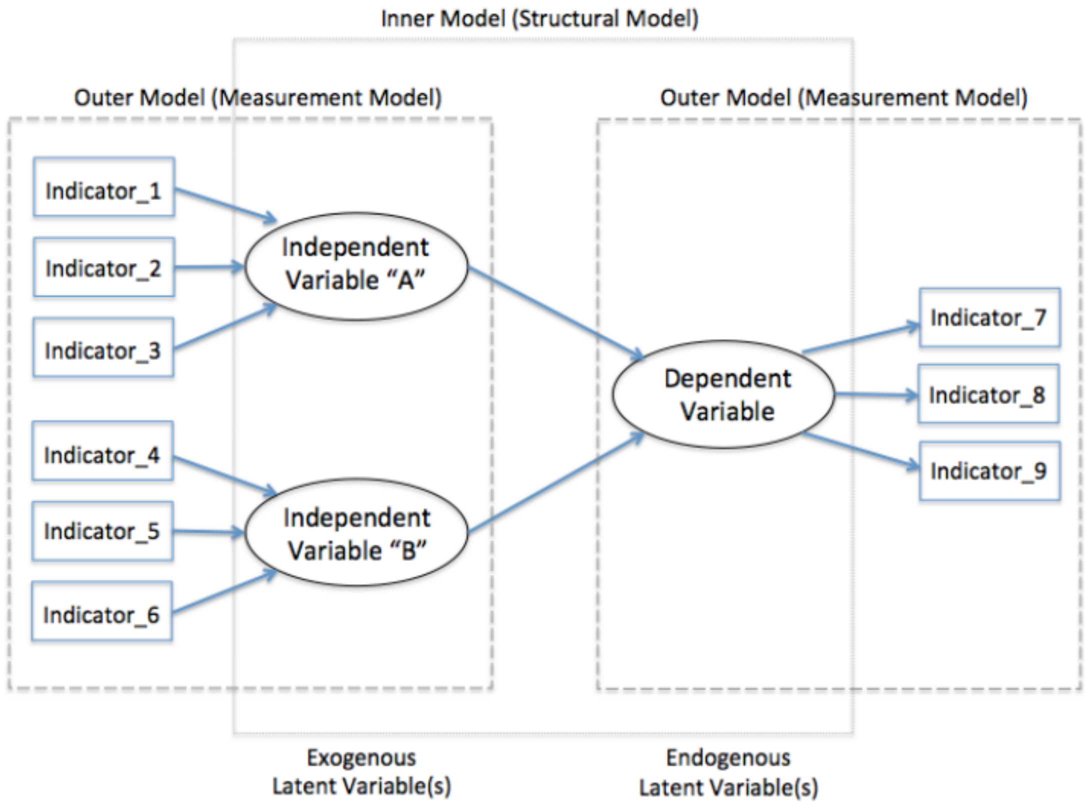

Figure 7: Relation between measurement and structural model
(Kwong & Wong, 2013, p. 2)

After introducing the two relevant measurement models for BI&A capacity and innovation capacity, the following chapter presents the developed research model, i.e., the structural model component concerned with the relationships between the three main latent variables of interest.

CHAPTER 3

RESEARCH MODEL AND HYPOTHESES

Structural equation modelling is composed of the measurement model(s) and the structural model. The previously introduced measurement models for BI&A capacity and innovation capacity measure these latent variables, while the structural model tests all the hypothetical relationships between the latent variables based on path analysis. We developed such a structural model to establish cause-effect relations between the three main variables of interest and thereby take up the two research questions of this thesis:

RQ1: What is the effect of BI&A capacity on innovation capacity?

RQ2: What is the specific influence of analytics maturity on BI&A capacity?

The developed structural research model can be seen in Figure 8 below. Due to its complexity, the full research model (structural model and measurement models) including all constructs, subconstructs and corresponding indicators can be found in Figure 13 in Appendix D.

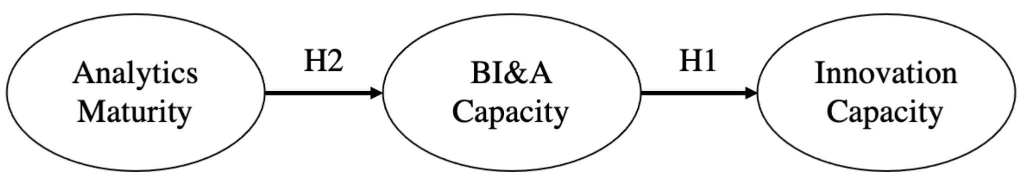

Figure 8: Structural research model and hypotheses

The structural model suggests that analytics maturity is directly linked to a firm's BI&A capacity that in turn directly impacts its innovation capacity. The nature of these relationships is theorized by two hypotheses that are derived on the following two pages. Here the first hypothesis H1 is related to the first research question RQ1 while the second hypothesis H2 is related to the second research question RQ2.

Link between BI&A Capacity and Innovation Capacity (RQ1 / H1)

Past studies already identified how important it is for firms to be able to sense and discern environmental information that can be transformed into new business opportunities, thus allowing the firm to consistently evolve and innovate (Bose, 2009; Chae, 2014; Wang & Dass, 2017). The collected data can further also help to identify new ways of uncovering smaller improvements to existing or completely new business opportunities (Ashrafi & Zare Ravasan, 2018; Sivarajah et al., 2017). BI&A is one enterprise application that firms use to develop such innovation capacity (March & Hevner, 2007). "The use of advanced [BI&A] tools allows firms to be more creative and test new ideas in a virtual environment before introducing them in reality" (Ashrafi et al., 2019, p. 4; see also Rud, 2009).

A study by Bayo-Moriones and Lera-López (2007) supports this by uncovering that the main reasons for firms to implement BI&A is to increase their innovation capacity. Comparably, Işik et al. (2013) report that firms increasingly use BI&A capabilities to discover new opportunities which in turn form the basis to make entrepreneurial decisions, e.g., about the development of new products or services. Appropriate use of BI&A enables firms to sense environmental changes, transform new cognitive knowledge into actionable insights and thus drive managerial decision making (Y. Chen & Lin, 2021). Herewith, companies get an improved and more holistic understanding of their internal and external environments (Chung & Tseng, 2012).

Duan et al. (2020) consider themselves the first to theoretically and empirically investigate the relationship between business analytics and innovation. Their results suggest that BA "directly improves environmental scanning which in turn helps to enhance a company's innovation" (Duan et al., 2020, p. 673). Another recent study suggests that "BA capabilities strongly impact a firm's agility through an increase in information quality and innovative capability" (Ashrafi et al., 2019, p. 1). Although both studies used somewhat different concept operationalizations, their findings suggest that BI&A indeed positively impacts innovation in organizations. At the same time, the novelty of their research further emphasizes the need for more extensive research into this relation, specifically the relation between BI&A capacity and innovation capacity as defined in this thesis. Thus, and considering the above discussion, we postulate the following first hypothesis which is directly related to the first research question (RQ1):

H1: BI&A capacity positively impacts innovation capacity.

Link between Analytics Maturity and BI&A Capacity (RQ2 / H2)

The assessment of the BI&A capacity construct as introduced before does not consider the analytics maturity stage achieved in organizations, i.e., descriptive, diagnostic, predictive, or prescriptive. Since the increase in maturity stages allows organizations to answer questions from "What happened?" (hindsight) to "What should we do?" (foresight), we posit that this maturity is likely to have a positive impact on the more abstract BI&A capacity of a firm. Through more mature analytics in the form of more advanced tools and methods like forecasts and simulations, the sensing, transforming, and driving capabilities and hence the overall BI&A capacity will be extended and sharpened. We expect the shift from hindsight to foresight to positively impact decision-making, especially around radical product or service innovations. As for such innovations to be successful, we argue it is imperative to have foresight, i.e., understand what customers would want to see in the future. Thus, we posit that analytics maturity acts as an exogenous variable in the path model that positively affects the endogenous BI&A capacity construct. Directly related to the second research question (RQ2), we therefore formulate the following second hypothesis:

H2: Analytics maturity has a positive effect on BI&A capacity.

After presenting the structural research model and deriving the associated hypotheses based on previous research, the next chapter lays out the research method used to evaluate the model. It addresses the data collection process, model constructs and their respective measurement as well as the data analysis procedure. The findings outlined in the data analysis in Chapter 6 then allow us to accept or reject the proposed hypotheses.

CHAPTER 4

RESEARCH METHOD

4.1 Data Collection and Sample Size

The proposed research model was tested using primary data from an online survey. Due to the organizational nature of this investigation, so-called key informants were solicited to provide information about the use of BI&A and innovation practices in their companies. In organizational IS research, the practice of using key informants is commonly employed (Benlian et al., 2011). For the purpose of this study, a key informant was defined as a BI&A and innovation subject matter expert in a managerial or executive function within his or her organization. Since this research aims at exploring BI&A capacity as an enabler of innovation capacity, a survey was distributed among managers (e.g., IT-, BI-, Innovation managers) and executives (e.g., CIOs, CTOs) that are expected to be knowledgeable about the use and benefits of BI&A and innovation practices in their organization.

In the absence of a readily available sampling frame and given that employees in management positions are difficult to reach, snowball sampling, a non-probability convenience sampling technique, was employed to collect data for this research. This technique has been proven to be suitable in research where the target population is difficult to reach as is the case with business executives (Nadler et al., 2015). Hereby, respondents are obtained via contacts of the researcher's social network and the referrals made by these (Nadler et al., 2015). The technique is therefore also known as network sampling or chain-referral.

The professional networks of the author served as the initial sampling seeds and invitations were sent to five LinkedIn interest groups focused on BI&A and related concepts as well as three LinkedIn user groups consisting of IT Managers, CIOs, and CTOs respectively. Invitees were given 14 days to complete the survey and were asked to forward the survey to other potential participants in order to improve sample diversity.

Primary data for this research was collected using a survey instrument which was published using the online survey tool Qualtrics which was provided access to by Leiden University. The collected data was then exported from Qualtrics and imported in SmartPLS 3.0 for the analysis as outlined further below.

4.2 Model Constructs and Measurement

All measurement models were validated by their corresponding researchers before and therefore initially adopted without changes. As part of the data analysis in Chapter 5 both measurement models will however be evaluated based on multiple criteria. In total, the survey consists of 53 questions (see Appendix C). However, the order of the individual indicators or survey questions was changed in comparison to the original studies. It is argued that such variety in the answer layout avoids “straight-lining” and conformity of the responses, thereby reducing the common method bias (Podsakoff et al., 2003).

4.2.1 Endogenous Variable: BI&A Capacity

As suggested by Chen and Lin (2021), the first endogenous variable of the structural model “BI&A capacity” will be measured as a second-order hierarchical construct made up of the three underlying capabilities or first-order constructs sense, transform, and drive, which have been extracted and identified as internal mechanics of

BI&A. These three first-order constructs are measured reflectively by a total of 26 items. In turn, the second-order BI&A capacity construct is a more general concept that is represented reflectively by its three subconstructs. Thus, the aggregated second-order construct is defined as type I reflective-reflective model (see Becker et al., 2012; Cheah et al., 2019; Ringle et al., 2012).

The construct is measured with the 26-item scale developed by Chen and Lin (2021) which is based on prior research. Respondents were asked to indicate the extent to which they agree with the 26 statements about the use and perceived benefit of BI&A in their company. The items are assessed on a five-point Likert scale ranging from 1 = "Strongly disagree" to 5 = "Strongly agree". The survey items can be found in Appendix C.

4.2.2 Endogenous Variable: Innovation Capacity

As introduced and defined by Doroodian et al. (2014), the final endogenous variable of the structural model "innovation capacity" is concerned with the continuous improvement of the four underlying innovation capabilities, contributing to the overall firm's potential to innovate. It is assumed that the continuity of improvement is achieved through "continuous innovation efforts or engaging with innovation practices in a company." (Doroodian et al., 2014, p. 3). Thus, Doroodian et al. (2014) consider innovation practices as the measures for assessing a firm's innovation capacity in their research model.

The scale was also designed as a second-order hierarchical construct consisting of the four first-order constructs KTM, IDM, PDV, and COM which have been identified as main dimensions or underlying capabilities of innovation capacity. These four subconstructs are measured reflectively by a total of 19 items, the innovation practices. In turn, the second-order innovation capacity construct is reflectively measured by its four subconstructs. Thus, the aggregated second-order construct was also specified as type I reflective-reflective model (see Becker et al., 2012; Cheah et al., 2019; Ringle et al., 2012). As shown in Appendix C, participants were asked to specify the extent to which the different innovation practices are institutionalized in their company. All items are measured on a five-point Likert scale, ranging from 1 = "Not at all" to 5 = "Extensively".

4.2.3 Exogenous Variable: Analytics Maturity

The third variable in the structural research model "analytics maturity" is regarded as a first-order latent construct. It is measured reflectively by a four-item scale developed by Duan et al. (2020) that was adopted from previous work by Delen and Demirkan (2013) and Kiron et al. (2012). As shown in Appendix C the participants were asked to indicate the extent to which their company established the four types of analytics, i.e., descriptive, diagnostic, predictive, and prescriptive. The items are measured on a five-point Likert scale ranging from 1 = "Not at all" to 5 = "Extensively" to arrive at one combined analytics maturity score.

The variable is not considered categorical because in business practice, companies do not only use one of the four types of analytics. Even when they advance along the analytics maturity path, the prior stages will remain in use. In fact, the four types of analytics co-exist and complement each other. However, with an increasing extent of usage and utilization of multiple analytics types, the organization's overall analytics maturity increases. Therefore, a combined score was derived for this research.

4.2.4 Control Variables

To take into consideration possible differences between firms that could impact the dependent variable innovation capacity, firm size, firm age, and industry sector have been identified as suitable control variables for the research model. They have been widely used in previous studies on related topics (e.g., Božič & Dimovski, 2019b; Duan et al., 2020; Kulkarni et al., 2017). Therefore, we extend the structural research model shown in Figure 8 by including those three control variables. This results in an updated model that can be seen in Figure 9 below. Following the illustration, arguments for choosing the specific control variables are given.

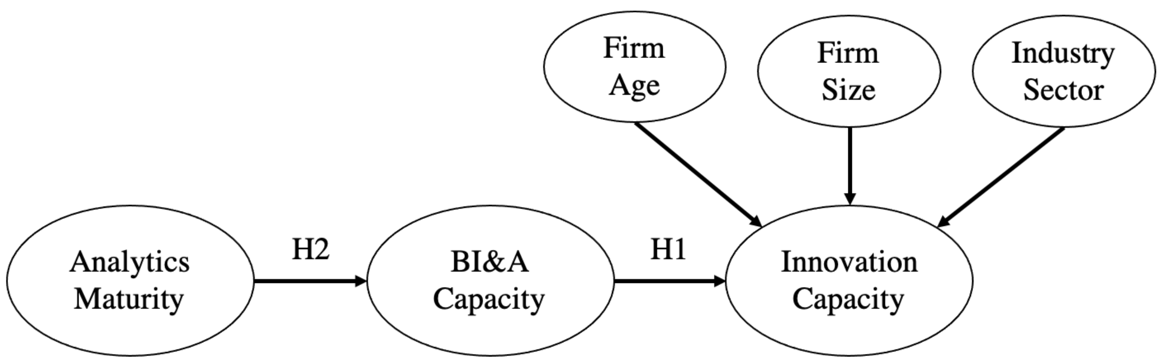

Figure 9: Structural research model extended control variables

Firstly, **firm size** is included as a control variable as it may have an effect on the innovation practices in a company (Damanpour, 1991) and its flexibility. Prior studies have shown that firm size can affect firm adaptation and growth through inertia and difficulty related to information processing (He & Wong, 2004; Tushman et al., 1985). In addition, firm size was found to impact innovative ambidexterity (Andriopoulos & Lewis, 2009; Uotila et al., 2009). Therefore, in order to account for the difference in firm size, a variable with a value of 1 for small firms, 2 for medium firms, and 3 for large firms, is used.

Secondly, **firm ag**e is included as a second control variable as it might impact a firm's innovation capacity because older firms had more time to build up resources, define organizational routines and develop capabilities (J. B. Barney, 1991; Eisenhardt & Martin, 2000). However, older firms are more prone to internal inertia (Leonard-Barton, 1992) that stifles innovation. Thus, respondents were also asked to indicate the number of years their company has been in business.

Thirdly, the **industry sector** was found to be associated with discrepancies in firm adaptation and performance (He & Wong, 2004; Lubatkin et al., 2006). Since adaptation is a crucial element in innovation efforts, the industry sector is likely to influence the innovation capacity in the research model. Therefore, the two broad industry sectors of manufacturing and services will be controlled by including an industry dummy variable (1 = manufacturing, 2 = services) in the model to explicitly control for unobserved industry idiosyncrasies.

4.3 Data Analysis Method

Structural equation modelling was applied in this study because it allows to include latent variables such as BI&A capacity that are measured by their related observed indicators (Joseph F. Hair et al., 2017). In addition, this approach has been found fitting especially for analyzing survey data in the past (Joseph F. Hair et al., 2017). There are two types of SEM, first the covariance-based SEM, which is used for the purpose of theory testing, confirmation, or comparison of alternative theories (Joseph F. Hair et al., 2017). And then there is the partial least squares (PLS) SEM which is used to predict target constructs or identify "driver" constructs that can be used to develop theory in exploratory research (Joseph F. Hair et al., 2017). The latter aims to explain the variance in the dependent variable when examining research models (Joseph F. Hair et al., 2017).

There are several arguments supporting the decision to use PLS-SEM as the most appropriate method in this thesis. Firstly, PLS-SEM is better suited than CB-SEM if the research goal is to predict key target constructs and when the research model is more complex, i.e., has many (higher-order) constructs and many indicators (Joseph F. Hair et al., 2017). Secondly, with this method there are less constraints regarding the possible model complexity, survey sample size and its distributional properties (Joe F. Hair et al., 2011). While PLS-SEM is a regression-based approach, it is nonparametric in nature and does therefore not make assumptions regarding the data distribution (Joseph F. Hair et al., 2017). Thus, it allows the analysis of small sample sizes and nonnormally distributed data (Joseph F. Hair et al., 2017).

As outlined before, both BI&A capacity (BIACAP) and innovation capacity (INVCAP) are measured as reflective-reflective second-order constructs. Thus, and following Sarstedt et al.'s (2019) guidelines of hierarchical modelling, both the repeated indicator approach and the two-stage approach can be used to identify the higher-order constructs (Sarstedt et al., 2019). As the repeated indicator approach is shown to produce smaller biases in the estimation of the higher-order construct's measurement model (Sarstedt et al., 2019), this approach was used for the data analysis in PLS-SEM.

In this approach, all indicators of the first-order components are assigned to the second-order constructs (Sarstedt et al., 2019), i.e., BIACAP and INVCAP. For example, BIACAP consists of three lower-order components (i.e., sense, transform, drive), each measured with eight, six and 12 indicators respectively. The higher-order component

BIACAP is then also measured with the same total 26 indicators as the lower-order components. The PLS-SEM algorithm uses either Mode A or Mode B to estimate the measurement model depending on its specification. It is recommended to use Mode A for all reflectively specified higher-order constructs, i.e., reflective-reflective and reflective-formative types (Sarstedt et al., 2019). Thus, all constructs were modelled as Mode A "reflective" in SmartPLS 3.0. Non-parametric bootstrapping with 1,000 replications was then performed to obtain the standard errors for all estimators (Joe F. Hair et al., 2011).

In conclusion, the analysis of the proposed research model was conducted with the software SmartPLS 3.0, following the recent guidelines of Sarstedt et al. (2019) on validating higher-order constructs in PLS-SEM. The guidelines suggest assessing multiple criteria for the measurement model and the structural model. Those will be outlined in detail and evaluated in the next chapter, after the descriptive statistics in regard to the company and respondent profile of the survey participants.

CHAPTER 5

DATA ANALYSIS AND RESULTS

5.1 Descriptive Statistics

After removing incomplete survey responses, 70 complete survey responses remained. All 70 respondents worked at unique companies; therefore, the number of company profiles also equals 70. A descriptive analysis was performed on multiple company demographics such as number of employees, duration of years the company has been in business and the industry sector.

Two thirds of responding companies reported to operate in the services industry and most of them have been in business for up to 20 years. The majority of companies employs over 250 employees, followed by 34% of companies that reported to only employ up to 50 employees. Table 3 summarizes the company profile.

No. of employees	%	Firm age	%	Industry sector	%
< 50	34	< 10 years	44	Manufacturing	33
50 - 250	21	10 - 20 years	41	Services	67
> 250	44	> 20 years	14		

Table 3: Company profile

In addition, descriptive analysis was performed on the current job position or role of respondents in their firm. The top roles represented included informed experts (26%), CTOs (23%), and IT managers (21%). While the seniority of informed experts and respondents who checked "Other" is not known, most respondents can clearly be assigned to middle management or executive positions in their firm. Therefore, it can be assumed that these respondents were able to address the survey questions. Table 4 on the next page summarizes the respondent profile.

Positions	%
CIO	9
CTO	23
IT manager	21
BI manager	11
Informed Expert	26
Other	10

Table 4: Respondent profile

5.2 Evaluation of the Measurement Model

A confirmatory factor analysis was conducted to assess the reliability and validity of the hierarchical constructs BIACAP and INVCAP and the one-dimensional analytics maturity (AM) construct. Specifically, the measurement model was tested for indicator reliability, internal consistency reliability, convergent validity and discriminant validity, following Sarstedt et al. (2019).

Indicator Reliability

First, factor loadings were examined to test for the indicator reliability of the reflective constructs. The factor loading of each indicator "should be equal to or above 0.7, such that the shared variance between the construct and its indicators is greater than the variance of the error term" (Knapp, 2018, p. 29; see also Fornell & Larcker, 1981). After the initial analysis, only 27 items exceed this threshold, while the other 22 were slightly below 0.7. Hair et al. (2017) recommend removing indicators scoring between the values of 0.4 and 0.7 only if they negatively affect the overall average variance extracted (AVE) of their related construct. Since this was the case, the following 13 indicators were removed from the model: BIA_D2, BIA_D3, BIA_D4, BIA_D5, BIA_D9, BIA_D10, BIA_D11, BIA_T1, BIA_T3, BIA_T5, KTM_PDV2, KTM_PDV4, KTM_COM2. The corresponding questionnaire statements to each mentioned indicator ID can be found in

Appendix C. The following analysis steps are now based on this updated model with the reduced number of indicators.

The reliability and validity assessment of the two second-order constructs BIACAP and INVCAP draws on their relationship with their lower-order components. Consequently, the reflective relationships between the BIACAP construct and its lower-order components sense, transform, and drive, are interpreted as loadings although they appear as path coefficients in the path model. The same applies to the INVCAP construct. All outer loadings can be found in Table 5 and seen in Figure 13 in Appendix D.

Internal Consistency Reliability

In a next step, the internal consistency of the constructs was assessed by examining the Cronbach's Alpha and the composite reliability. In general, internal consistency assesses the correlation between multiple indicators in a questionnaire that are intended to measure the same construct or variable (Joseph F. Hair et al., 2017). The recommended threshold for Cronbach's Alpha is > 0.7 (Joseph F. Hair et al., 2017) and all variables surpassed it. In addition, all variables also surpassed the recommended minimum value for composite reliability (> 0.7) (Joseph F. Hair et al., 2017). Thus, it can be concluded that the internal consistency of all reflective latent variables in the measurement model is given.

Convergent Validity

Next, the convergent validity of each reflective construct was evaluated by examining the average variance extracted. The AVE value of a construct shows, on average, how much variations in its indicators can be explained by the construct or latent variable (Joseph F. Hair et al., 2017). On the other hand, the remainder of the variance can hence be credited to the measurement error (Chin et al., 2010). While the AVE values for the lower-order constructs are automatically calculated by SmartPLS 3.0, those values had to be manually calculated for the higher-order constructs following the steps outlined by Sarstedt et al. (2019).

Each construct should have an AVE value of above 0.5 to confirm its convergent validity, according to Fornell and Larcker (1981). As displayed in Table 5 this was the case for all constructs except for transform, drive, and PDV with AVE values of 0.473, 0.398, and 0.464 accordingly. This means, the indicators of these constructs explain slightly more errors than the variance in these constructs. Hence, the convergent validity of the measurement model is not completely given.

Discriminant Validity

Both convergent validity and discriminant validity are subcategories of construct validity, and they work together. While the convergent validity measured by the AVE shows a convergence between similar constructs, the discriminant validity shows a divergence between dissimilar constructs (Joseph F. Hair et al., 2017).

There are multiple ways to assess discriminant validity. In the past, the Fornell-Larcker criterion and the examination of cross-loadings were primarily used for that purpose. However, a recent study found that "both the Fornell-Larcker criterion and the assessment of the cross-loadings are insufficiently sensitive to detect discriminant validity problems" (Henseler et al., 2015. p. 120). Instead, Henseler et al. (2015) proposed an alternative measurement for discriminant validity, the heterotrait-monotrait ratio (HTMT). The HTMT "ratio is based on the average of the correlations of indicators across constructs measuring different phenomena relative to the average of the correlations of indicators within the same construct" (M. Gupta & George, 2016, p. 1057). The recommended threshold for HTMT values is <0.85 to provide sufficient support for discriminant validity (Sarstedt et al., 2019).

The results in Table 6 show that this criterion was met for all constructs. However, the discriminant validity between the second-order constructs BIACAP and INVCAP and their respective first-order constructs is not considered. Since the measurement model of the higher-order components repeat the indicators of its lower-order components, a violation of discriminant validity between these constructs is expected (Sarstedt et al., 2019). The according values are marked with “-“ in Table 6.

Summary of the Measurement Model Evaluation

In conclusion, almost all measurement model evaluation criteria for the reflectively measured constructs have been met, providing support for their reliability and validity. However, the three first-order constructs transform, drive and PDV have not fully met the AVE criterion for convergent validity. This limitation will be further addressed in Chapter 6. All before-mentioned reliability and validity criteria for the reflective constructs based on the reduced set of indicators can be seen in Table 5 on the next page.

Factors	Loadings β	Cronbach's α	Composite reliability ρC	Average variance extracted (AVE)
AM		0.881	0.882	0.651
AM1	0.775			
AM2	0.845			
AM3	0.781			
AM4	0.824			
BIACAP		0.789	0.762	0.650
Sensing	0.994	0.951	0.951	0.707
BIA_S1	0.886			
BIA_S2	0.820			
BIA_S3	0.870			
BIA_S4	0.792			
BIA_S5	0.849			
BIA_S6	0.860			
BIA_S7	0.826			
BIA_S8	0.820			
Transforming	0.749	0.729	0.729	0.473
BIA_T2	0.684			
BIA_T4	0.700			
BIA_T6	0.680			
Driving	0.636	0.726	0.725	0.398
BIA_D1	0.597			
BIA_D6	0.687			
BIA_D7	0.621			
BIA_D8	0.616			
INVCAP		0.812	0.786	0.631
KTM	0.796	0.844	0.842	0.575
INV_KTM1	0.765			
INV_KTM2	0.859			
INV_KTM3	0.612			
INV_KTM4	0.775			
IDM	0.291	0.928	0.927	0.719
INV_IDM1	0.915			
INV_IDM2	0.837			
INV_IDM3	0.831			
INV_IDM4	0.801			
INV_IDM5	0.852			
PDV	0.905	0.723	0.722	0.464
INV_PDV1	0.682			

Factors	Loadings β	Cronbach's α	Composite reliability ρC	Average variance extracted (AVE)
INV_PDV3	0.663			
INV_PDV5	0.698			
COM	0.992	0.814	0.814	0.523
INV_COM1	0.707			
INV_COM3	0.796			
INV_COM4	0.693			
INV_COM5	0.691			

Table 5: Reliability and validity statistics

	AM	**BIACAP**	COM	Drive	IDM	**INVCAP**	KTM	PDV	Sense	Transform
AM										
BIACAP	0.282									
COM	0.414	0.796								
Drive	0.286	-	0.734							
IDM	0.399	0.208	0.182	0.437						
INVCAP	0.516	0.810	-	0.686	-					
KTM	0.428	0.804	0.473	0.230	0.266	-				
PDV	0.139	0.684	0.522	0.618	0.691	-	0.181			
Sense	0.225	-	0.518	0.249	0.069	0.613	0.793	0.544		
Transform	0.131	-	0.839	0.712	0.132	0.650	0.592	0.416	0.379	

Note: Bold used for second-order constructs.

Table 6: Discriminant validity assessment using the HTMT criterion

5.3 Evaluation of the Structural Model and Hypothesis Testing

The structural model (outer model) evaluates the path relationships between the three different latent variables. This thesis is interested in the direct relationship between AM and BIACAP and the direct relationship between BIACAP and INVCAP. Hair et al. (2019) recommend assessing the following standard criteria: multicollinearity, path coefficients, the coefficient of determination (R^2), the blindfolding-based cross-validated redundancy measure Q^2, and the model's out-of-sample predictive power. Following Hair et al. (2017), bootstrapping procedure, using 1,000 iterations and no sign changes, was run to examine the significance of the relationships. Further, all bootstrap confidence intervals were calculated using the software SmartPLS 3.0 based on a two-tailed test at a significance level of 1% (Joseph F. Hair et al., 2017).

Multicollinearity

To check for the first criterion multicollineary, the outer Variance Inflation Factor (VIF) values of all predictor variables in the research model were examined. The recommended restrictive cut-off value is 3.3. (Petter et al., 2007) and as shown in Table 7 all values are below it, indicating that there are no multicollinearity issues in the model.

	BIACAP	INVCAP
AM	1.000	
BIACAP		1.011
FirmAge		1.014
FirmSize		1.031
IndustrySector		1.036

Table 7: VIF values

Path Coefficients

In a next step, the significance of the direct relationships between AM-BIACAP and BIACAP-INVCAP in the structural model was tested. For that matter, the path coefficients between the constructs were examined. Path coefficient values "are usually between -1 and +1, indicating a strongly negative and strongly positive relationship between the variables." (Knapp, 2018, p. 35). Values close to 0 on the other hand, indicate a weak relationship.

SmartPLS 3.0 computed a two-tailed test for the t- and p-values at a significance level of 1% to test path coefficients significance. For the relationship between AM-BIACAP (β = 0.107) the results showed a t-value of 1.028 and a p-value of 0.304, indicating that there is no significant relationship between the two variables. This means, that hypothesis H2 is rejected. On the other hand, the results show that there is a strong positive relationship between BIACAP-INVCAP (β = 0.813) with a t-value of 21.515 and p-value of 0.000 (rounded value, not exactly 0), emphasizing its significance. Hence, the main hypothesis of interest H1 is supported. As depicted in Table 8, the path coefficients of all three control variables were close to zero, while the corresponding low t- and high p-values further indicated the non-significance of them.

	Path Coefficient β	Sample Mean	Standard Deviation	T-Statistics	P-Values
AM -> BIACAP	**0.107**	0.100	0.104	1.028	**0.304**
BIACAP -> INVCAP	**0.813**	0.819	0.038	21.515	**0.000**
FirmAge -> INVCAP	-0.004	-0.008	0.079	0.048	0.962
FirmSize -> INVCAP	-0.051	-0.050	0.065	0.790	0.430
IndustrySector -> INVCAP	-0.015	-0.009	0.078	0.195	0.846

Table 8: Structural model path coefficients

Below, the path coefficients β and their p-values (in brackets) of the structural model can be seen in Figure 10 as displayed in SmartPLS 3.0. This alternative visual presentation allows for a better understanding of the structural path model.

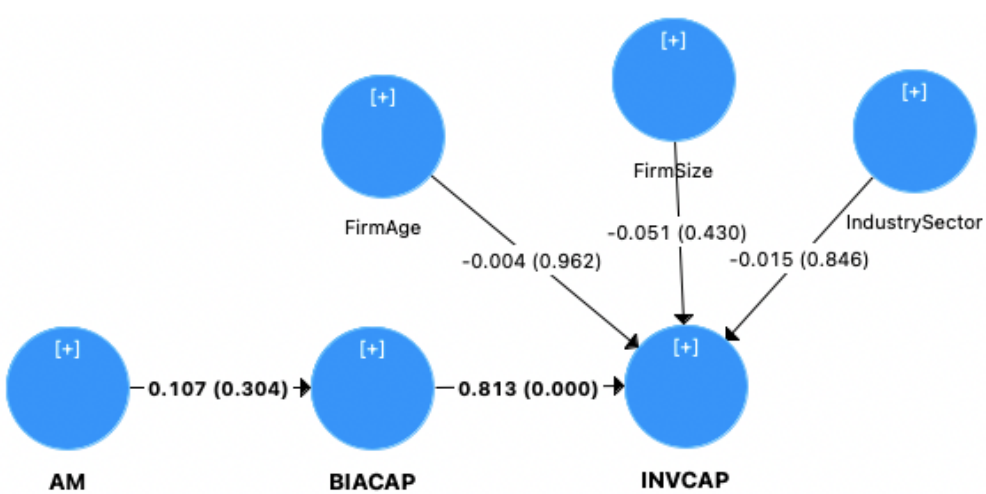

Figure 10: Path analysis results as displayed in SmartPLS 3.0

Explanatory Power

Next, the explanatory power, also referred to as in-sample predictive power, of the structural model was examined with the determination coefficient R^2. The "combined effect of all exogenous latent variables on the endogenous latent variable" is reflected by this coefficient (Knapp, 2018, p. 37). According to Hair et al. (2011) a value of 0.75 can be interpreted as a strong, a value of 0.50 as a moderate, and a value of 0.25 as a weak predictive power for endogenous latent variables.

The R^2 value of BIACAP (0.011) indicates that the model has no explanatory power for this endogenous variable. On the other hand, the R^2 value of INVCAP (0.668) does indicate a moderate to substantial explanatory power for this variable (see Table 9).

Effect Size

Cohens f^2 represents the effect size of the predictor variables, here AM and BIACAP, on the dependent variables, here BIACAP and INVCAP, in the research model (J. Cohen, 1992). Threshold values of 0.02 for a small, 0.15 for a medium, and 0.35 for a large effect are recommended in literature (J. Cohen, 1992; Joseph F. Hair et al., 2017).

The f^2 value for AM-BIACAP (0.012) indicates a neglectable small effect, while the f^2 value of BIACAP-INVCAP (1.968) represents a very large effect (see Table 9). Looking at the f^2 values of the three control variables, one can see that they do not have any significant effect. In conclusion, only BIACAP has a large effect contributing to the explanatory power (R^2) of the INVCAP construct.

Predictive Relevance

The next criterion to validate the structural model is its predictive relevance, measured by Stone-Geissers Q^2 value (Joseph F. Hair et al., 2017). This value indicates the out-of-sample predictive power opposed to the in-sample predictive power measured by R^2 (Joseph F. Hair et al., 2017). As the name suggests, models with a predictive relevance ($Q^2 > 0$), are able to predict new data that was originally not in the sample when the structural model was estimated.

To determine the Q^2 values, the so-called blindfolding procedure is run in SmartPLS 3.0. "Blindfolding is a sample reuse technique that omits every *d*th data point in the endogenous construct's indicators and estimates the parameters with the remaining data points." (Joseph F. Hair et al., 2017, p. 178). Hair et al. (2017) recommend an omission distance D between 5-10. As part of this analysis, the blindfolding procedure was run with the omission distance D = 6.

The positive Q^2 values for BIACAP (0.007) and INVCAP (0.646) indicate a predictive relevance for both of these two endogenous constructs. At the same time, it is evident that there is only a high out-of-sample predictive relevance for the latter construct INVCAP in the path model.

	R^2	f^2	Q^2
BIACAP	0.011		0.007
INVCAP	0.668		0.646
AM -> BIACAP		0.012	
BIACAP -> INVCAP		1.968	

Table 9: Explanatory power, effect size and predictive relevance

After the evaluation of the measurement model and structural model based on the range of recommended criteria outlined above, the next chapter interprets the statistical findings and discusses them in the context of the two research questions. It further emphasizes the key research contributions, managerial implications, limitations of the study, and avenues for future research.

CHAPTER 6

DISCUSSION

6.1 Key Findings and Research Contribution

Building on the literature streams of business intelligence and analytics, innovation, and dynamic capabilities, this study empirically tested the impact of analytics maturity and BI&A capacity as antecedents of innovation capacity. The statistical evaluation has provided moderate support for the proposed research model.

RQ1: What is the effect of BI&A capacity on innovation capacity?

Specifically, the direct relationship between an organization's BI&A capacity and its innovation capacity was found to be statistically significant ($\beta = 0.813$; $p = 0.000$). Hence, a firm's BI&A capacity has a strong positive impact on its innovation capacity, supporting hypothesis H1. This improves the understanding of this direct relationship, because previous research by Duan et al. (2020) only tested an indirect relationship. In addition, this result supports the work of Ashrafi et al. (2019) who identified a direct positive relationship between a firm's BA capabilities and innovative capability.

The findings support the theory that the dynamic sensing, transforming, and driving capabilities together generate an organization-wide BI&A capacity that contributes to a firm's innovation capacity. Through the ability to collect data and transform it into useful insights, business decisions can be made "data-driven" instead of relying on executives' instinct. This process was found to significantly affect an organization's ability to continuously innovate, specifically around products and services. By using insights gained from data and sensing environmental changes like customer demands, firms can better understand their customers and are thereby enabled to provide meaningful new products and services. Although the investigation of the link between innovation capacity and competitive advantage was out of scope in this thesis, this relationship has already been sufficiently researched and proven (Crossan & Apaydin, 2010; Francis & Bessant, 2005). Thus, it can be derived that building an organization-wide BI&A capacity ultimately leads to competitive advantage through the increase in a firm's innovation capacity. Further, the results provide support to prior findings that externally obtained information is becoming increasingly important to achieve a competitive advantage (Lane et al., 2006; Lichtenthaler, 2009), which is related to the sensing capability of the BI&A capacity.

RQ2: What is the specific influence of analytics maturity on BI&A capacity?

While the achieved analytics maturity stage in an organization was theorized to positively impact its more abstract BI&A capacity, this investigated relationship was found to be nonsignificant in this study ($\beta = 0.107$; $p = 0.304$). Thus, hypothesis H2 is rejected. This result suggests that firms utilizing any degree of BI&A have the ability to sense environmental changes, transform data into knowledge, and drive decision-making, regardless of the achieved analytics maturity stage. However, the small sample size ($n = 70$) in this study could have led to this result and further research into this relationship may lead to other results.

It is not very unexpected that the control variables company size, company age, industry type and respondent's job role have no effect on innovation capacity. In this study, all their path coefficients and p-values were found to be nonsignificant. Although there has been extensive research on these control variables in the context of innovation, previous results have been contrary and multifaceted (Duan et al., 2020).

In conclusion, the high R^2 value of 0.668 indicates that the proposed model explains more than two thirds of the variance in the endogenous variable innovation capacity. As a result, the research model has a moderate to substantial explanatory or in-sample predictive power for innovation capacity. However, since the model cannot explain 100% of the variance, it may be interesting to examine additional possible predictors of innovation capacity in a firm.

Research contributions

This study makes a few important contributions to research. Firstly, until now, there has been little theoretical understanding about the direct link between BI&A capacity and innovation capacity and no empirical evidence confirming it. With a new specific approach to characterize this relationship, this study aided to close this research gap by linking BI&A capacity to innovation capacity with a cross-sectional perspective. In contrast to previous work from the strategic management community based on case studies (e.g., Kunc & O'Brien, 2019), our approach is built on survey data.

By developing and analyzing a structural model linking analytics maturity, BI&A capacity, and innovation capacity, we were able to characterize this relationship and answer the first research question RQ1. By uncovering a positive, direct, and significant impact, this study characterizes and therefore extends the knowledge of the relationship between an organization's BI&A capacity and its innovation capacity. The research model examines how BI&A capacity contributes to innovation capacity based on the dynamic capabilities perspective and therefore provides a very focused theoretical understanding of BI&A's impact to researchers and practitioners.

Secondly, this study makes original contributions by theorizing the effect of analytics maturity on the more abstract BI&A capacity as this has not yet been researched. It thereby provides a first step in investigating this relationship. Although, the theorized positive relationship was not confirmed by this study, the theoretical contributions offer important insights into the developments of BI&A over the last two decades. Those findings help to stress the important role of developing a high analytics maturity in order to improve BI&A's impact and pose an avenue for future research.

6.2 Managerial Implications

This study's results provide useful advice for managers and executives responsible for BI&A initiatives in their companies.

Firstly, the findings evidently prove the importance of building an organization-wide BI&A capacity as a driver for innovation capacity to ultimately increase competitive advantage. It shows that decision-makers can depend on data-driven insights rather than their gut instincts. For this to become a reality, companies should encourage staff to use such data-based insights when developing improved or new products and services and to base decisions on them.

Secondly, the theoretical considerations regarding the achieved analytics maturity stage indicate the importance of investing into the related advanced analytics techniques and methods to increase the overall BI&A capacity, although this effect was not confirmed in this study. Prior research has however found that a low analytics maturity is an impediment of developing a BI&A capacity that delivers value (Gartner Inc., 2018). In addition, the shift from simple to advanced analytics allows firms to move from generating hindsight to foresight based on their data. This is expected to be of increasing importance in the future to stay competitive.

6.3 Limitations and Avenues for Future Research

Limitations of the study

This thesis has several limitations. Firstly, the model only focuses on BI&A capacity's impact on innovation capacity from a dynamic capabilities perspective. Therefore, the proposed research model is missing potential additional predictors of innovation capacity and cannot (and was not intended to) predict 100% of the variance in the latent construct. There are a range of other factors such as leadership styles, corporate strategies and other management efforts that may influence a firm's ability to innovate continuously. This should be kept in mind when applying the proposed model to predict a firm's innovation capacity.

This study's data has only used firm size, firm age, industry sector and respondent's job title as control variables, thus potentially neglected the impact of other firm characteristics on the link between BI&A capacity and innovation capacity. Future research should therefore include additional firm characteristics and explore their impact on the innovation capacity of organizations. In addition, three subconstructs of the research model had an AVE value slightly below the threshold of 0.5, indicating that the convergent validity of the model is not completely given. This could be due to chance and because of the small sample size but emphasizes the need for additional attention when copying the model.

Secondly, the generalizability and representativeness of the findings is limited due to the use of the snowball-sampling technique (Nadler et al., 2015). Due to the difficulties in reaching respondents in managerial and executive positions, this approach seemed most fitting. However, in order to increase the statistical inference, future studies should be run with probability sampling. In addition, the sample size of 70 is very small and limits the significance of the interpreted findings. Further, the firm's industry sector is considerably biased towards companies operating in the services industry (67%) and the geographical location of the firms was not collected in the survey. Future studies should therefore distinguish between more specific industries and additionally collect the firm's geographical location in order to increase the generalizability of the findings. Although the control variables all had insignificant effects on INVCAP, a further investigation with a more homogenously distributed sample should be conducted.

Thirdly, this thesis collected data at one time, such that a longitudinal perspective on the changes in the organization's BI&A and innovation capacities is not possible to analyze. Therefore, future research should collect data at different points in time, allowing the analysis of changes in BI&A capacity and how these changes impact the organization's innovation capacity in the long run.

Further, this study relies on a single data source and may therefore be subject to common method bias. That is, self-reported measures of the same respondents have been collected for the independent and dependent variables (Podsakoff et al., 2003). This may lead to leniency bias and social desirability bias. Since snowball-sampling was used to collect data, this thesis's findings might be contingent on leniency bias, the probability that respondents, depending on whether they like the researcher, answer in accordance with an anticipated turnout. As the professional network of the researcher acted as a starting point for the data collection method, some respondents might have answered in such a way they expected the researcher to anticipate. By stating that respondents should answer to the best of their knowledge and belief at the beginning of the survey, the leniency bias was tried to be mitigated (Podsakoff et al., 2003).

In addition, managers and executives often do not want to harm their firm's image and reputation, potentially affecting their answers. This so-called social desirability bias was tried to be mitigated by ensuring that all answers are treated confidentially. In future research, this could further be reduced by including more than one respondent per firm.

Finally, this study did not consider varying market dynamics and competitive threats which could influence the way a firm engages in innovation practices, influencing their innovation capacity (Duan et al., 2020). These factors could further act as an exogenous driver of innovation capacity and therefore future studies should control for environmental dynamism to ensure the findings can be compared under a range of dissimilar market conditions.

Avenues for future research

This study poses a few avenues for future research. The proposed research model is only concerned with innovation capacity around new product, service, and process innovation, but neglects other innovation fields such as organizational and marketing innovations or completely new business models. Examination of the model in other innovation fields in future research could therefore yield interesting results (Duan et al., 2020). Next, the rejected hypothesis H2 suggests further investigation of the link between analytics maturity and BI&A capacity, possibly through a different conceptualization with other measurement items (Król & Zdonek, 2020).

In addition, researchers should also consider employing a qualitative approach in contrast to the quantitative approach used in this study. For example, case studies or interviews with professional experts could yield more detailed knowledge about how the organization-wide BI&A capacity contributes to its innovation capacity (Duan et al., 2020). Further, by collecting data at different points of time, researchers could incorporate a longitudinal approach allowing them to track and compare changes in the variables of interest over a certain time period (Knapp, 2018). This could yield interesting results when looking at one firm that has not yet invested (much) in developing a BI&A capacity but has planned to do so. If data was to be collected for this firm before and after their BI&A investments one could further verify the effect of those efforts on the firm's innovation capacity.

CHAPTER 7

CONCLUSION

This study is the first to link BI&A capacity directly to innovation capacity, and to characterize and evaluate how that relation may operate, because previous work used different conceptualizations (Ashrafi et al., 2019) or investigated an indirect relationship (Duan et al., 2020). In addition, we are the first to adapt the multi-dimensional BI&A capacity construct recently suggested by Chen and Lin (2021) emphasizing the systemic forces endogenous to BI&A rather than technical aspects (e.g., Işik et al., 2013; Kulkarni et al., 2017). We further extended their research efforts by characterizing the effect of BI&A capacity on innovation capacity in contrast to firm performance and by additionally considering analytics maturity in our research model (Y. Chen & Lin, 2021).

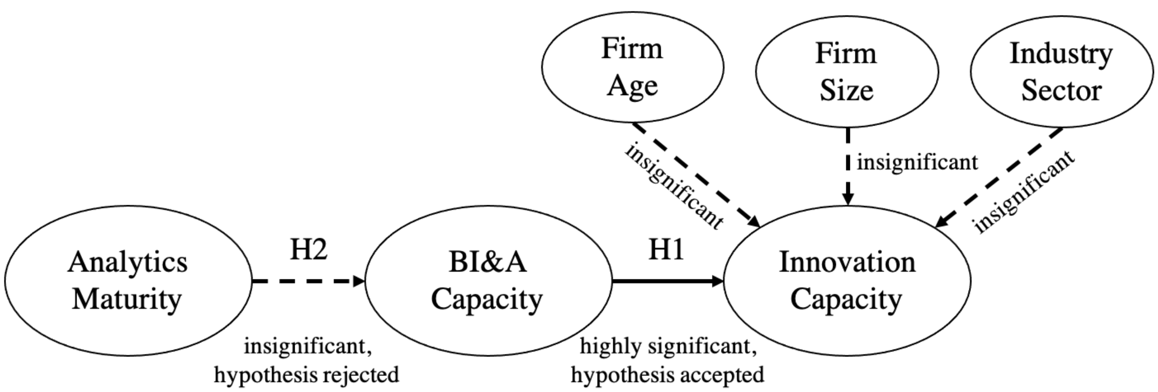

Figure 11: Structural research model with path results

The empirical evidence allowed us to formulate answers to both research questions in this thesis. In regard to the first research question (RQ1) it can be concluded that a firm's BI&A capacity has a strong and positive direct effect on its innovation capacity (as seen in Figure 11 on the right side). This relationship was found to be highly significant and the corresponding hypothesis H1 was therefore supported. This impact of BI&A can be explained by the firm's underlying dynamic sensing, transforming, and driving capabilities. These help to improve a firm's innovation capacity in terms of new products and services, thus ultimately leading to better competitive advantage (Crossan & Apaydin, 2010; Doroodian et al., 2014). Specifically the sensing capability allows a firm to acquire external information which has been identified as one factor to strengthen a firm's competitive advantage in prior research (Lane et al., 2006; Lichtenthaler, 2009) and is therefore supported by this thesis.

In regard to the second research question (RQ2), the gathered data did not reveal a specific impact of the achieved analytics maturity stage in a firm on its BI&A capacity (as it can be seen directly in Figure 11 on the left side). Due to the insignificant path coefficient, the corresponding hypothesis H2 was rejected. However, based on the theoretical derivations, we firmly believe that organizations should still pay particular attention to the role of their analytics maturity if they want to maximize the potential impact on their innovation capacity, stemmed from investments in business intelligence and analytics. This conclusion is in line with research by analyst group Gartner who identified low analytics maturity as an impediment for developing an organization-wide BI&A capacity (Gartner Inc., 2018).

Our novel research model based on quantitative survey data in contrast to Kunc and O'Brien (2019) case studies revealed new aspects about the benefits of BI&A. Based on our findings we formulated answers to the two research questions that can be interpreted in such a way that insights-driven enterprises can expect to develop more meaningful new products, processes, and services. This result can be achieved by sensing and discerning environmental changes, transforming them into valuable insights that are then used to drive business decisions around incremental and radical innovations. Therefore, managers and executives responsible for BI&A initiatives can feel confident to encourage the use of BI&A, as this this demonstrated how and to what extent it impacts a firm's innovation capacity.

Although our approach can be seen as a real unique attempt to consider the specific impact of analytics maturity on BI&A capacity in a conceptual model, the results did not yield such. Therefore, future study should specifically investigate the link between analytics maturity and BI&A capacity again, e.g., by using a different measurement conceptualization or a qualitative and longitudinal research approach. Due to the continuing advances in BI&A development outlined in our extensive literature review such as augmented analytics (Prat, 2019), social analytics, visual data discovery, and data lakes (e.g., Eggert & Alberts, 2020; Gartner Inc., 2019), this link remains of utmost interest in years to come. The expected development of new analytics maturity models, focusing on specific sectors or businesses (Król & Zdonek, 2020), could then yield different results when investigating the specific effect of analytics maturity on BI&A capacity.

APPENDICES

APPENDIX A

DEVELOPMENTS OF BI&A

Minitrack phase	Key themes and their relevance (10% or above)	Key concepts (abstract)	Key insights
1990-1996	Information (100%) EIS (66%) System (53%) Data (50%) Problem (18%) Approach (14%) Knowledge (10%)	System Use Information Executives Management Data	• Strong focus on business/organizational aspects and applications of EIS rather than technology • Sentiment analysis: both positive (i.e., favorable: 51%) and negative (unfavorable: 49%) experiences with EIS reported.
1997-2003	Data (100%) Distributed (94%) System (82%) User (71%) Information (41%) Metadata (20%) Analysis (15%) Case (14%)	Data System User Database Warehouse Support Query	• Strong focus on technical aspects of DW • Prominent concepts such as "database" and "query" related to data storage and processing • Key themes: performance related issues, metrics, and metadata • Prominence of case studies
2004-2011	Information (100%) Data (73%) Value (25%) Quality (24%) Knowledge (19%) Dimension (15%)	Data Use Information Business Process System	• A very visible shift from data bases and DW to information (including the challenges of turning data into information) • Key themes "value" and "knowledge" indicated challenges in deriving business value of BI technology and turning insights into knowledge • Prominence of conceptual modeling papers and data quality (to a lesser extent)
2012-2017	Data (100%) Business (95%) Information (94%) BI (62%) Model (27%) Value (13%) Customer (12%)	Data Use Process Systems Information Model Management Analysis	• BI remained among the key themes but interpretations became quite diverse • Although present on the concept map, "big data" did not appear among the most prominent concepts and themes • The "big data" concept related to "theory" because researches had concerns about the lack of theoretical foundations of big data and focused on building new (big data) theories • This phase included more literature review papers than any other phase (primarily in relation to big data)

Table 10: Key BI&A concepts and themes observed across different phases
(Marjanovic & Dinter, 2018, p. 787)

Technologies	Analytics	Data storage	Data management	Visualization						
	52	2	14	7						
Analysis techniques	Econometrics	Linguistics	Optimization	Statistics	Non analytics					
	13	5	28	6	23					
Analytics maturity	Descriptive (Explorative)	Diagnostic	Predictive	Prescriptive	Non analytics					
	25	8	18	1	23					
Emerging research area	Human computer interaction	Data science foundations	Text analytics	Social analytics	Network analytics	Mobile analytics				
	6	3	2	13	25	26				
Research method & evaluation	Deductive analysis	Simulation	Reference modeling	Action research	Prototyping	Ethnography	Case study	Grounded theory	Cross-sectional study	Lab or field experiment
	34	13	20	2	16	3	22	0	12	21
Application area	E-Government and politics	Market intelligence	Security & public safety	Smart health	Smart industry	IoT	Application area independent			
	2	23	5	5	19	10	11			
Data privacy	Not addressed	Risks & problems mentioned	Introduction of a solution							
	52	13	11							

Figure 12: Summarized results of BI&A 3.0 literature review
(Eggert & Alberts, 2020, p. 699)

APPENDIX B

CONSTRUCT DEFINITIONS

Construct	**Definition**	**References**
Business Intelligence and Analytics (BI&A)	BI&A refers "to the techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand its business and market and make timely business decisions."	Chen et al. (2012), p. 1166
Analytics Maturity (AM)	Analytics maturity refers to the type of analytics dominantly used in organization, i.e., descriptive, diagnostic, predictive or prescriptive.	Król and Zdonek (2020)
Dynamic Capability	Dynamic capability is defined as "the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments".	Teece et al. (1997)
BI&A Capacity (BIACAP)	BI&A capacity is defined as the ability, that exists at present, to sense environmental changes, transform information into appropriate actions, and then drive business firms to reach organizational consensus in decision making and re-engineering processes to achieve business goals.	Chen and Lin (2021)
Sensing Capability	Sensing capability is defined as the ability to dynamically configure business processes to assist optimization of resource allocation through timely and accurate identification of the changing environment.	Chen and Lin (2021)
Transforming Capability	Transforming capability is defined as the ability to continuously integrate and create new knowledge for developing new products or upgrading or reengineering operational processes.	Chen and Lin (2021)
Driving Capability	Driving capability is defined as the ability to make use of knowledge to drive product innovation, process re-engineering, decision-making optimization, and to reach cognitive consensus among stakeholders.	Chen and Lin (2021)

Construct	Definition	References
Innovation Capacity (INVCAP)	Innovation capacity is defined as "a continuous improvement of the overall capability of firms to generate innovation."	Hogan et al. (2011), p. 1266
Knowledge and Technology Management Capability (KTM)	KTM capability is defined as the ability to assimilate, adapt to, and transform acquired knowledge and technology.	Doroodian et al. (2014)
Idea Management Capability (IDM	IDM capability is defined as the ability to screen for and acquire innovative ideas.	Doroodian et al. (2014)
Project Development Capability (PDV)	PDV capability is defined as the ability to use high-tech tools and equipment for designing, engineering, prototyping, and testing.	Doroodian et al. (2014)
Commercialization Capability (COM)	COM capability is defined as the ability to analyze markets and competitors and to commercialize innovations.	Doroodian et al. (2014)

Table 11: Construct definitions

APPENDIX C

CONSTRUCTS AND INDICATORS OF THE STUDY

Construct	Subconstruct	ID	Indicator
BI&A Capacity (BIACAP) 2nd order construct (reflective-reflective)	**Sense** 1st order construct (reflective)	BIA_S1	BI&A can effectively discover the opportunity to raise or improve efficiency.
		BIA_S2	BI&A can identify the business models and operating processes to be improved.
		BIA_S3	BI&A assists to better understand the internal opportunity or threats in the firm.
		BIA_S4	BI&A can diagnosis the deficiencies in the existing operating processes.
		BIA_S5	BI&A can capture the opportunity and threat in general business practices.
		BIA_S6	BI&A can search for the influential factors for strategic changes in responding to volatile environment.
		BIA_S7	BI&A enables better understand the organizational environment of a business firm.
		BIA_S8	BI&A generates more operational solutions in terms of its forward looking analysis ability.
	Transform 1st order construct (reflective)	BIA_T1	BI&A assists to set a favorable position and explore new opportunity in the turbulent environment.
		BIA_T2	BI&A assists to continuously create or absorb new knowledge, develop new products or innovative business processes.
		BIA_T3	BI&A assists to discern and integrate the new knowledge through exogenous sources of external network and social capital.
		BIA_T4	BI&A can prompt reallocation of available resources in line with the strategic goals and fully utilize the knowledge for organizational changes.
		BIA_T5	BI&A improves the capability of optimizing allocation and utilization of resources in light of new business practices.
		BIA_T6	BI&A assists to enhance organizational learning to capture, create and utilize new capability.
	Drive 1st order construct (reflective)	BIA_D1	BI&A matches the interest of all stakeholders to reach cognitive consensus on responding measures.
		BIA_D2	BI&A assists to build up consensus of stakeholders on the responses to environmental changes.
		BIA_D3	BI&A assists to reach consensus of stakeholders on making business decisions.
		BIA_D4	BI&A assists to build up consensus among all stakeholders.
		BIA_D5	BI&A matches with rational business planning.
		BIA_D6	BI&A improves the efficiency of business planning.
		BIA_D7	BI&A can align strategic planning and changes in business environment.
		BIA_D8	BI&A ensures the practicability of business action plans.
		BIA_D9	BI&A ensures the effectiveness of decision making on operational planning.
		BIA_D10	BI&A ensures the guiding mechanics of business decisions.
		BIA_D11	BI&A ensures the timeliness of best action planning.
		BIA_D12	BI&A ensures the executability of rational business decisions.
Innovation Capacity (INVCAP) 2nd order construct (reflective-reflective)	**KTM** 1st order construct (reflective)	INV_KTM1	Encouraging and supporting the informal R&D, internal technological efforts, and learning activities
		INV_KTM2	Knowledge and technology acquisition
		INV_KTM3	Continuous improvement of firm's ability to assimilate, adapt to, and transform acquired knowledge and technology
		INV_KTM4	Monitoring and evaluating technology trends
		INV_KTM5	Managing internal and external as well as tacit and explicit firm's knowledge to generate innovations
	IDM 1st order construct (reflective)	INV_IDM1	Using different techniques of creativity and idea generation
		INV_IDM2	Innovative ideas acquisition through networking and external relations
		INV_IDM3	Idea screening through the firm overall and innovation strategy
		INV_IDM4	Idea screening through multicriteria feasibility study

Construct	Subconstruct	ID	Indicator
	PDV 1st order construct (reflective)	INV_PDV1	Creating cross-functional project teams
		INV_PDV2	Improving capabilities of designing, engineering, prototyping, and testing
		INV_PDV3	Using a comprehensive system of innovation project management
		INV_PDV4	Using high-tech tools and equipment
		INV_PDV5	Internal and external networking and cooperation
	COM 1st order construct (reflective)	INV_COM1	Market analysis and monitoring
		INV_COM2	To improve proficiency of personnel and adequacy of organization's facilities in the commercialization area
		INV_COM3	Adherence to a commercialization schedule and commitment to formal post-launch reviews
		INV_COM4	Using of joint venturing and other financing methods to commercialize innovations
		INV_COM5	Monitoring competitors
Analytics Maturity 1st order construct (reflective)		AM1	Descriptive (What has happened and what is happening?): e.g., uses business intelligence and data mining to provide the context of and trending information on past or current events.
		AM2	Diagnostic (Why did it happen and why is it happening?): e.g., uses drill-down, data discovery, and data mining to examine data or content to answer the question "why did it happen?".
		AM3	Predictive analytics (What could happen?): e.g., uses statistical models and forecasts to provide an accurate projection of the future happenings and the reasoning as to why.
		AM4	Prescriptive analytics (What should we do?): e.g., uses optimisation and simulation to recommend one or more courses of action and show the likely outcome of each decision.
Control Variables	**Firm Size**	CON1	How many people are employed at your company?
	Firm Age	CON2	How long has your company been in business?
	Industry Sector	CON3	In which industry sector is your business?
Filter Question	**Job Position**	FIL1	Which of the following best describes your job position?

Table 12: Constructs and indicators of the study

(Y. Chen & Lin, 2021, p. 13; Doroodian et al., 2014, p. 9; Duan et al., 2020, p. 679)

APPENDIX D

SMARTPLS PATH MODEL

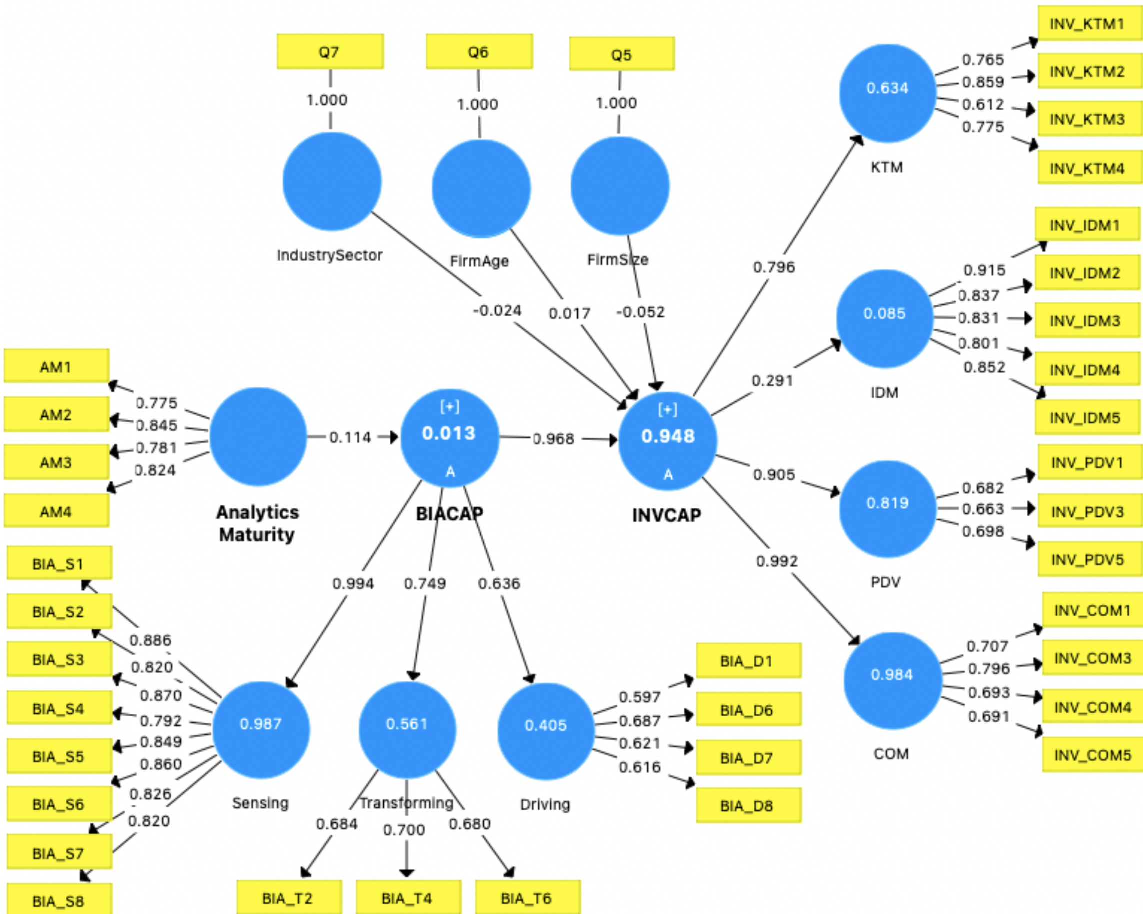

Figure 13: Complete path model as in SmartPLS 3.0

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