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Adoption and Governance of AI-Powered Dashboards in Executive-Level Decision-Making

Information System Science

Master's thesis

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AI-powered dashboards are business intelligence tools that collect and present data in a comprehensible manner to enhance decision-making. The integration of artificial intelligence (AI) in data-driven decision-making (DDDM) processes is continuously increasing in modern organizations, however, current research examining AI-powered dashboards does not address the deployment of the technology. To complement prior research, this thesis aims to provide a foundation for the implementation of AI-powered dashboards by investigating the current dashboard best practices, as well as the adoption and governance of AI-powered dashboards in the context of executive decision-making. The concepts of DDDM and AI function as a foundation regarding the purpose and functionality of AI-powered dashboards, whereas IT governance provides a basis for their adoption and governance. The research methodology encompasses a review of scientific literature addressing these concepts to enable the proposal of two distinct theoretical frameworks addressing the adoption and governance of AI-powered dashboards.

The results of this study highlight three critical areas regarding AI-powered dashboards: current best practices, adoption processes, and governance. Best practices show that AI-enabled dashboards are dynamic and versatile BI tools that enhance decision-making and operational efficiency through detailed visualizations and data analysis. Concerning adoption, the study emphasizes the importance of selecting a suitable framework tailored to organizational needs, suggesting that a combination of existing models might often be necessary to integrate AI and BI within organizational environments effectively. Results addressing the governance of AI-powered dashboards emphasize the importance of BI and AI governance. Although the development of AI governance frameworks is still in its early stages compared to BI and IT governance, the findings suggest that adopting flexible and diverse governance structures enables organizations to manage the security, transparency, and accuracy risks associated with AI technologies.

Keywords: Dashboard, Business intelligence, Artificial intelligence, Data-driven decision-making.

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Dashboardit ovat liiketoimintatiedon hallinnassa hyödynnettäviä työkaluja, jotka tehostavat päätöksentekoa analysoimalla ja visualisoimalla dataa. Huolimatta tekoälyn integroinnin jatkuvasta lisääntymisestä päätöksentekoprosesseissa, tieteellinen kirjallisuus ei käsittele tekoälyä hyödyntävien dashboardien käyttöönottoa. Tämän tutkielman tarkoituksena on täydentää aiempaa tutkimusta tutkimalla nykyhetkellä käytössä olevia dashboardeja sekä AI-käyttöisten dashboardien käyttöönottoa ja hallintoa ylimmän johdon päätöksenteon kontekstissa. Dataan perustuva päätöksenteko ja tekoäly luovat perustan AI-käyttöisten dashboardien käytölle ja toimivuudelle. Informaatioteknologian hallinto taas tarjoaa perustan AI-käyttöisten dashboardien hallitsemiselle. Tutkimusmenetelmänä toimii näitä konsepteja käsittelevä kirjallisuuskatsaus, johon perustuen tutkielma ehdottaa kahta erillistä teoreettista viitekehystä liittyen AI-käyttöisten dashboardien käyttöönottoon ja hallintoon.

Tutkielman löydökset jakautuvat kolmeen AI-käyttöisiä dashboardeja käsittelevään aihepiiriin: Nykyiset parhaat käytännöt, käyttöönoton prosessit sekä hallinto. Tulokset viittaavat siihen, että AI-käyttöiset ohjauspaneelit ovat dynaamisia ja monipuolisia työkaluja, jotka tehostavat päätöksentekoa ja operatiivista tehokkuutta yksityiskohtaisten visualisointien ja datan analysoinnin avulla. Käyttöönottoa käsittelevät löydökset korostavat sopivan viitekehyksen valitsemista organisaation tarpeisiin ja ympäristöön perustuen sekä mahdollista tarvetta yhdistää lukuisia tarjolla olevia käyttöönottomalleja sopivan ratkaisun löytämiseksi. Hallintoa käsittelevät löydökset puolestaan korostavat tekoälyn huomioimista osana informaatioteknologian hallintoa. Löydösten perusteella joustavien ja monimuotoisten hallintorakenteiden omaksuminen voi auttaa hallitsemaan AI-teknologioiden turvallisuuteen, läpinäkyvyyteen ja täsmällisyyteen liittyviä riskejä.

Avainsanat: Dashboard, tekoäly, liiketoimintatieto, päätöksenteko.

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LIST OF ABBREVIATIONS

Abbreviation	Definition
AI	Artificial Intelligence
AI RMF	AI Risk Management Framework Core
ANN	Artificial Neural Networks
BA	Business Analytics
BI	Business Intelligence
COBIT	Control Objectives for Information and Related Technologies
CV	Computer Vision
DBMS	Database Management System
DDDM	Data-driven Decision making
DOI	Diffusion of Innovation Theory
DSS	Decision Support Systems
EIS	Executive Information Systems
GDSS	Group Decision Support Systems
ISACA	Information Systems Audit and Control Association
IT	Information Technology
ITIL	IT Infrastructure Library
IoT	Internet of Things
MIS	Management Information Systems
ML	Machine Learning
NIST	National Institution of Standards and Technology
NLP	Natural Language Processing
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
SAC	SAP Analytics Cloud
SAP DB	SAP Digital Boardroom
SAP HANA	SAP High-performance Analytic Appliance
SME	Structural Equation Modeling
SQL	Structured Query Language
TAM	The Technology Acceptance Model
TOE	Technology Organization Environment
TPB	Theory of Planned Behaviour

1 Introduction

1.1 Research area and motivation

Informed and reliable decision-making has always been a crucial factor regarding organizational functionality. Data has revolutionized decision-making during the 21st century. As a result, data-driven decision-making (DDDM) has emerged as an essential part of strategic planning in modern organizations. The significance of DDDM is based on its capability to improve the quality of decisions throughout an organization. Recruiting new employees, optimizing a marketing strategy, managing risks, and selling products are incidents occurring on various levels and areas of an organization, nevertheless, each incident can benefit from DDDM. In addition to DDDM, the utilization of Artificial Intelligence (AI) has recently gained significant attention in organizational environments. The rapid technological development of AI techniques has resulted in advanced tools that enable organizations to pursue various opportunities while seeking a competitive advantage. Researching and utilizing the combination of DDDM and AI is a critical element to consider in modern organizations aiming to leverage the potential benefits enabled by these concepts.

Dashboards are commonly utilized business intelligence (BI) tools that promote DDDM by comprehensively describing contexts such as organizations, departments, and projects. They accelerate decision-making and simplify complex situations by displaying comprehensible visualizations based on relevant data. Big data, which refers to the exponential expansion of the volume, variety, and velocity of data during the concurrent digital age, is one of the most influential recent technological developments. Traditional dashboards possess limited capabilities regarding the processing and analysis of data which prevents them from effectively managing large and complex data sets. As a result, the efficiency and accuracy of traditional dashboards are decreasing.

AI offers potential solutions to the difficulties posed by big data in DDDM by utilizing machine learning (ML), natural language processing (NLP), and predictive analytics among various other methods. The integration of dashboards and modern AI techniques enables the development of automated dashboards based on large real-time datasets. AI-powered dashboards could enhance the DDDM efforts of an organization by improving

elements such as operational efficiency and decision-making on various organizational levels.

1.2 Research questions and research gap

The objective of this thesis is to study the adoption and governance of AI-powered dashboards as an element within the DDDM efforts of an organization. To reach this objective, the study aims to create an understanding of AI-powered dashboards as a concept and determine how the use of the technology could effectively be adopted and governed by the executives of an enterprise in the complex internal and external environments of modern organizations. The following research questions have been formulated to address this area of research:

1. What are the current best practices for dashboards, and do they utilize AI?
2. If AI is utilized, how does it affect the adoption of dashboards from the perspective of executives?
3. How does the potential utilization of AI affect the governance of dashboards?

The first research question addresses dashboards as a DDDM solution and includes determining the current state of best practice dashboards as well as studying whether AI techniques are being utilized during their development. The second research question addresses integral factors influencing the adoption of AI-powered dashboards from the perspective of the executives of an organization. Lastly, the third research question addresses the governance of AI-powered dashboards from the same perspective.

Interest in research involving BI and AI has increased in recent years as a result of new advanced AI tools and the opportunities provided by them. Studies addressing the combination of BI and AI examine concepts such as predictive analytics, NLP, and ML in the context of DDDM. Prior research provides a holistic view of AI and dashboards as individual subjects. However, AI-powered dashboards as a specific concept have not been thoroughly researched. While the literature on AI-powered dashboards is limited, research on the topic does exist to a certain extent. Current literature includes research on the role of AI in dashboard customization and the use of AI-powered dashboards in the contexts of health care and cyber security for instance. The area of research in question however lacks studies addressing the adoption and governance of AI-powered

dashboards. The absence of studies exploring this research direction possibly functions as an obstacle preventing a more extensive deployment of the technology in organizational environments. The perspective of top management is included in this study to provide a currently feasible context for the adoption and governance of AI-powered dashboards. The organization-wide adoption of AI-powered dashboards is not supported by current scientific literature, however, research examining the topic from the less complex perspective of top management could function as a foundation for future studies addressing the topic more extensively. In conclusion, further studies addressing AI-powered dashboards and their deployment can be considered a logical step in scientific literature examining the concepts of DDDM, BI, and AI.

1.3 Structure of the thesis

While the concepts of DDDM and AI function as the foundation of AI-powered dashboards, the literature on information technology (IT) governance provides a foundation for the adoption and governance of the technology. To answer the three research questions, this thesis reviews relevant scientific literature regarding the topics of DDDM, AI, and IT governance, to provide a comprehensive understanding of current research addressing AI-powered dashboards and the factors influencing their adoption and governance.

The introduction of this study leads to a literature review consisting of three main chapters that address the concepts of DDDM, AI, and IT governance. The literature review begins in Chapter 2 by presenting the general perceptions found in the scientific literature regarding the concept of DDDM. The definition of DDDM is followed by an examination of more specific segments within the broad concept of DDDM. These segments include BI, its predecessors decision support systems (DSS), and executive information systems (EIS) as well as dashboards and the role of big data in DDDM. Chapter 3 continues the literature review by initially addressing the scientific definition of AI, followed by an examination of the utilization of AI in DDDM. The chapter additionally reviews existing literature on AI-powered dashboards along with a practical method that enables the development of AI-powered dashboards in modern organizations through technology solutions provided by SAP SE. Examination of literature addressing IT governance finalizes the literature review in Chapter 4, which commences by addressing the scientific definition of IT governance. Subsequently, research and theoretical frameworks on the

adoption of new technology as well as the adoption of BI and AI technologies are reviewed. Finally, the literature review is completed through an examination of research addressing BI and AI governance.

Following the literature review, Chapter 5 presents the findings of the research. This segment of the study addresses the research questions by first providing an overview of the findings, followed by three subchapters that introduce these findings in more detail. Discussion takes place in Chapter 6 through interpretation of the findings introduced in Chapter 5, contribution, limitations of the thesis, and suggestions addressing potential directions of future research. Chapter 7 finalizes the study by summarizing and concluding its contents.

Tools utilizing AI techniques were utilized in this thesis to enhance the quality of the study in various aspects. Firstly, AI-driven tools were employed in the literature review to summarize information. This enabled the efficient review of scientific literature as well as the concise presentation of the derived information. Additionally, AI-powered tools were utilized throughout the thesis to reduce the occurrence of grammatical errors which enhances the readability of the written content in the study. Furthermore, due to the limited amount of research addressing AI-powered dashboards, AI tools were utilized to provide support in identifying relevant academic sources.

2 Data-Driven Decision Making (DDDM)

2.1 Definition of DDDM

Decisions are the conscious foundation of our actions. They can be based on observations, experience, or simply intuition among other reasons. The context where a decision is required can be uncomplicated or insignificant which indicates that effortless reasoning is adequate. In certain scenarios, however, the required decision could have significant effects based on its quality and accuracy. In these situations, a reliable and accurate decision-making process is critical for the outcome of the decision. DDDM refers to decisions made on the grounds of data analysis and its objective is to enable unbiased and accurate decision-making. Provost & Fawcett (2013) define DDDM as the practice of basing decisions on the analysis of data rather than purely on intuition. According to research conducted by Brynjolfsson et al. (2011), DDDM is a significant topic for organizations as it can enable increased operational efficiency and a competitive advantage through means such as increased productivity

A DDDM process consists of various components. Diván (2017) highlights data collection and data management as key elements of a DDDM process. Data collection refers to the practice of systematically collecting data from relevant internal and external sources whereas data management refers to actions taken to ensure an appropriate quality, security, and accessibility of the data. Data analysis, which includes the identification of patterns and trends alongside interpretation which refers to the practice of transforming data into information is also a key component of a DDDM process. (Borges et al. 2021) The components presented by Diván and Borges et al. cover the main parts of a DDDM process excluding the final component which is the actual decision-making.

Elgendy et al. (2022) propose a modern data-driven decision theory “DECAS” which provides a more comprehensive view of the topic by dividing the components of a DDDM-process into two groups: “elements of data-driven decision making” and “classical elements of decision making” (See Figure 1). Alongside these elements, the authors address significant considerations that should be taken into account during the process. Their theory highlights the importance of determining a degree of collaboration between human decision-makers and analytics as well as the creation of governance policies that manage risks and promote transparency and explainability in decision-

making. The final decision-making process should not be solely based on human decision-makers or analytics and the degree of collaboration between humans and technology should always be determined according to the context to attain high-quality decisions. Furthermore, the theory addresses the importance of continuous learning and improvement through evaluation and monitoring.

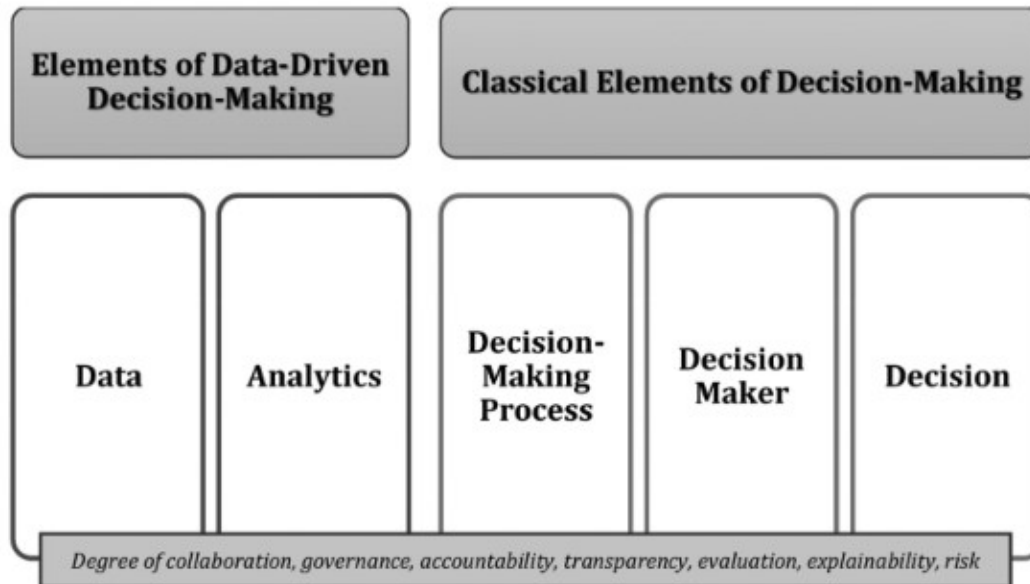


Figure 1 The elements of data-driven decision-making (Elgendy et al., 2022).

An IT infrastructure that includes information systems, hardware, and software, supports these key components and enables the functionality of a DDDM process in an organizational context (Elgendy et al., 2022).

2.2 Business intelligence (BI)

As a result of the global adoption of DDDM methods, modern business organizations generate and utilize data increasingly. Because of this, executives and managers are experiencing difficulties with finding the right information and forming a comprehensive understanding of it. BI systems and tools offer a solution to this challenge arising from the overload of business data. Lim et al. (2013) define BI as a concept that refers to the technologies, systems, practices, and applications analyzing critical business data to help an enterprise better understand its business and market. BI tools enable enterprises to release value from their data through data analytics which is one of the most integral elements within a DDDM process. Zohuri & Moghaddam (2020) largely share Lim's

perception of the concept of BI, although their definition includes a stronger emphasis on the ability of BI technologies to predict and forecast future trends based on historical data.

Business communities were first introduced to BI systems over 40 years ago. However, prior literature addresses the technology as DSS, EIS, and management information systems (MIS) (Thomsen, 2003). BI systems have developed rapidly during the 21st century and new technological developments such as cloud computing and big data analytics have significantly affected the degree of their utilization. As a result, the role of BI systems is considered critical in contemporary organizational environments (Niu et al., 2021). New technological developments are continuously impacting the state of BI technologies which encourages organizations to frequently improve their operational performance through new innovative solutions arising from the field of BI. (Lim et al., 2013).

The impact of utilizing BI technologies in business organizations is manifold. Smith & Doe (2007) researched the profit impact of BI and identified how the use of BI influences organizations and their way of conducting business. BI impacts decision-making processes by providing comprehensive and accurate information based on real-time data. Improved decision-making is one of the most significant benefits provided by BI technologies. Other integral subjects influenced by BI include operational performance and financial well-being. BI solutions promote operational efficiency through the automatization of data-related processes. Automatization allows organizations to allocate their resources more efficiently which results in time efficiency and optimized business processes. Operational efficiency enables the improvement of functions, such as inventory and supply chain management. By improving its functions, an enterprise can reduce the operating costs generated by these functions. Reduced operating expenses among other cost reductions contribute towards the financial well-being of an enterprise. Furthermore, the authors identify risk management, revenue, and strategic planning among organizational subjects impacted by the use of BI. The effectiveness of risk management can be increased by utilizing the predictive attributes possessed by BI tools. Revenue, on the other hand, can be enhanced by utilizingg BI technologies in customer analysis which enables the identification of integral customer segments. Additionally, trategic planning can be improved by the use of BI technologies that utilize predictive analytics to create comprehensive strategic plans based on historical and real-time data. (Smith & Doe 2007). The elements identified by Smith & Doe are general and occur in

most modern organizations, on various organizational levels. This indicates that BI could potentially impact most modern organizations presumed that it is implemented and utilized appropriately.

2.3 Decision support systems (DSS)

Arnott & Pervan (2005) describe DSSs as a collection of systems and processes that support and improve decision-making on multiple levels of an organization. To enable well-informed, effective, and efficient decision-making, DSSs utilize computational and analytical resources to derive insights from company data. DSSs are closely related to BI technologies as both concepts promote DDDM and share the same fundamental characteristics. Arnott & Pervan (2005) suggest that the concept of DSS includes EIS, group support systems, personal decision support systems, online analytical processing systems, data warehousing, and BI. Watson (2009) on the other hand proposes that the concept of BI includes all decision support applications which indicates that DSS would be a segment within the concept of BI. The scientific literature does not include a unanimous perception of the relationship between DSS and BI, however, the general perception in recent literature appears to support Watson's perspective on BI being the general concept that includes DSS and alternative decision support applications.

The term DSS first emerged during the 1970s when the computerization of operational aspects began to occur as a standard phenomenon in business organizations. The development of early DSSs attempted to overcome the limitations of MIS. It focused on the creation of a problem-solving environment where a human decision-maker deals with complex and unstructured details while an IT-based system provides support by managing structured elements regarding the context. (Arnott & Pervan, 2005). Following the early developments of DSS, the systems became more advanced, which has led researchers as well as organizations to consider them as essential factors regarding competitive advantage. They function beyond organizational boundaries and support decision-making by providing decision-makers with interactive graphical interfaces and real-time information (Watson, 2009). Alasiri & Salameh (2020) suggest that DSS perform well in unstructured and semi-structured decision situations that require significant human judgment. The authors propose an integrated BI/DSS solution that utilizes the data processing power of BI and the problem-solving qualities of DSS to create a comprehensive decision-support environment.

2.4 Executive information systems (EIS)

EIS refers to information systems specifically designed for the executives of an organization. The objective of EIS is to support strategic decision-making by providing comprehensive insights based on critical internal and external data. The system's functionality enables the top management of an organization to understand complex and broad situations with minimal effort which promotes fast and well-informed decision-making based on timely and accurate information. The systems can be adjusted to support various positions in upper management which means that relevant information will be displayed depending on the responsibilities of the user. (Leidner & Elam, 1995).

Leidner & Elam (1993) studied the impact of EIS on decision-making and suggested that using EIS regularly enables faster problem identification and the ability to react to these problems more efficiently and effectively. A further study on the impact of EIS on organizational design, intelligence, and decision-making by Leidner & Elam (1995) concurs with these initial findings. The study additionally proposes that the use of EIS does not significantly reduce the involvement of subordinates in executive decision-making. This indicates that the use of EIS increases the decision-making capabilities of upper management, however, it does not limit the flow of information between organizational levels regarding decision-making.

Yu et al. (2015) provide a more recent study on EIS, describing them as flexible tools that address the needs of upper management through functions such as analysis, scanning, and interpretation in unstructured contexts. The study states that EIS have the capability to support executives by performing these functions on relevant data. The data could include details about critical processes within the organization or external information such as news and regulations that might have an impact on the responsibilities of an executive. The study highlights the adaptability of EIS which enables the systems to provide support in various contexts depending on the responsibilities of the user.

2.5 Dashboards

A dashboard is a form of BI that offers a solution to information overload by initially collecting and analyzing relevant data regarding a specific context and then visualizing it. Yigitbasioglu & Velcu (2012) describe dashboards as inclusive packages that collect, summarize, and present information based on various sources. The authors additionally

state that although dashboards are a globally utilized decision support system, there is no universal agreement on their appearance. (Yigitbasioglu & Velcu, 2012) The absence of an established appearance could be explained by the fact that dashboards offer a suitable solution for a large variety of purposes which results in an endless number of potential dashboard designs supporting unique contexts.

2.5.1 Development

Although there is no universal agreement on the appearance of a dashboard, various theoretical frameworks address the process of creating a dashboard. Vilarinho et al. (2018) researched the development of dashboards for small and medium-sized enterprises to improve the performance of productive equipment and processes. The scope of their study is on operational dashboards, and it proposes a framework (See Figure 2.) that includes four phases describing the development process of dashboards.

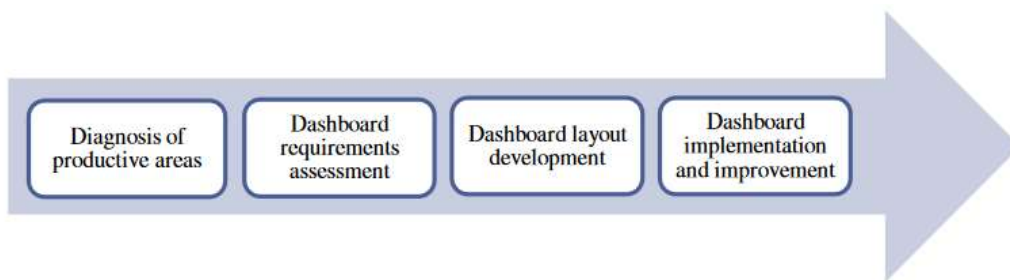


Figure 2. Defined phases for the dashboard development procedure. (Vilarinho et al., 2018).

The first phase addresses the diagnosis of productive areas, and it refers to understanding the context and identifying elements in need of improvement. Phase two includes the assessment of dashboard requirements. This indicates that requirements regarding the dashboard's functionality are determined in this phase, based on the diagnosis in phase one alongside relevant literature, and the capabilities of the project team. Phase three deals with the dashboard layout and its development which refers to the practice of converting identified requirements into concrete technical solutions. Phase four completes the process by addressing the implementation and improvement of the technology. The model guides organizations to identify required improvements by evaluating the functionality of the designed dashboard and monitoring its performance.

Vázquez-Ingelmo et al. (2019) provide a more comprehensive perspective on the development process of dashboards in a systematic literature review on information

dashboards and tailoring capabilities. The paper states that a single framework does not apply to all situations and highlights the importance of tailoring dashboards depending on the nature of the context. According to the study, an appropriate practice of tailoring a dashboard includes considering specific requirements, objectives, stakeholders, situations, and domains impacting it.

2.5.2 Utilization

According to Rasmussen et al. (2009), the use of dashboards can increase the efficiency, motivation, and performance of an employee. The tool allows employees to make more informed decisions and increases productivity by removing the need for redundant actions. It is possible to utilize dashboards as an individual BI solution, however, they are frequently deployed as a tool within a larger BI system incorporating various technologies. In the context of a larger BI system, dashboards can often be created and accessed through enterprise information portals. Through the collaboration of enterprise information portals and the BI system, employees create and share information across units and processes within an organization. Thus, creating an organization-wide network of knowledge. The authors propose the division of dashboards into three categories according to their purpose of use. Strategic dashboards address a larger, enterprise-wide context by supporting organizational alignment with strategic goals. Tactical dashboards on the other hand support the measuring of progress in key projects and initiatives. Lastly, operational dashboards support the monitoring of specific business activities which allows employees to fix problems or take advantage of opportunities on the department level. (Rasmussen et al., 2009).

Vázquez-Ingelmo et al. (2019) recognize the rising significance of information dashboards. The authors address the usefulness of adaptable dashboards as well as the challenges related to their design. The study divides tailoring into customization, personalization, and adaptation. Customization refers to adjustments performed by the user, personalization describes adjustments made by the system and adaptation refers to the modifications performed by the dashboard itself, based on user interactions. Challenges affecting the tailoring of dashboards are often rooted in resource constraints, the complexity of developing a dashboard design that can be implemented into varied environments as well as difficulties in determining an appropriate degree of user involvement. The paper proposes the use of AI technologies as a potential solution for

certain challenges related to the tailoring of dashboards. AI algorithms could improve system-driven personalization and real-time adaptation of dashboards. Additionally, issues regarding user involvement could be addressed by utilizing AI to analyze behavioral data. (Vázquez-Ingelmo et al., 2019).

Yigitbasioglu & Velcu (2012) studied the use of dashboards in the context of performance management. The study aims to discover how the use of dashboards influences the capability of sales managers in the context of performance management. The authors divide the use of dashboards into four functions: Monitoring, problem-solving, rationalizing decisions, and communicating coupled with consistency. The results of the study reveal that dashboards can effectively provide support for sales managers in performance management. However, the adoption rate of dashboards was lower than expected which indicates that a substantial portion of sales managers taking part in the research, chose to neglect the opportunity to utilize the technology. This could either indicate that the technology was too difficult to use, or the quality of the adoption process was not on an appropriate level. The study identifies that managers perceived the dashboard's ability to provide scenario analysis and information that is based on real-time data as integral strengths of the system.

2.6 Big data and DDDM

Scientific literature describes big data as one of the most significant technological developments in recent times. Within business communities, the benefits of adopting big data include increased profit and innovation, competitive advantages, and business growth. The broad variety of opportunities enabled by big data is considered a pivotal element in the contemporary highly digital business world. (Günther et al., 2017)

2.6.1 Definition of big data

Big data refers to large, complex, and varied datasets that are challenging to manage, process, and analyze through the use of traditional tools. Douglas Laney (2001) explains the concept of big data through three Vs: volume, variety, and velocity. By using these three words he defines big data as a phenomenon where large volumes of varied data are generated, captured, and processed at high velocity. To fit Laney's foundational definition into the present context, Ishwarappa & Anuradha (2015) introduce two additional Vs: value and veracity. Value refers to the ability to transform big data into tangible and

valuable results. Veracity on the other hand addresses the accuracy and quality of big data, which is not self-evident considering the nature of the original three Vs: volume, variety, and velocity. Sources such as sensors, mobile phones, social media, and online transactions are continuously contributing to the expansion of big data. (Sagioglu & Sinanc, 2013) The internet of things (IoT) refers to a network of devices that function as a connecting piece between the physical and digital worlds. The IoT network continuously utilizes sensors to generate data, which makes it a focal factor regarding the existence and expansion of big data. (Misra et al., 2020).

2.6.2 Challenges and opportunities of utilizing big data in DDDM

Bhadani & Jothimani (2016) researched the challenges, opportunities, and realities of big data. The authors studied various contexts and identified numerous opportunities arising from big data analytics. These opportunities include increased performance in marketing and insurance tailoring through personalization, better decision-making for investments in banking, and increased quality in product development. There is no denying that the opportunities enabled by big data are significant, however, acknowledging the challenges and risks of big data is equally important. Khan et al. (2014) conducted a study on the technologies, opportunities, and challenges revolving around big data and its adoption. Their paper highlights data integrity, data capture, data storage, data processing, and data inconsistencies as substantial data-related challenges. Additional challenges regarding the adoption of big data include privacy concerns, scalability, and handling of unstructured data. To manage these challenges, organizations are initially required to acknowledge them, which is followed by research addressing the challenges in the unique context of the organization. Subsequently, the development and adoption of new data management policies, measures, tools, and techniques can be conducted to deal with the challenges arising from big data. Hadoop is one of the most widely recognized data analysis tools in the context of big data analytics and its functionality is based on a distributed file system and the MapReduce architecture. The distributed file system splits data into smaller entities and distributes them across multiple nodes to ensure high availability. The MapReduce architecture enables the analysis of large datasets by promoting scalability through parallel processing that consists of two phases: The “Map” phase which processes and transforms input data into key-value pairs, and the “Reduce” phase which combines the key-value pairs into an output. (Khan et al., 2014).

3 Artificial Intelligence (AI)

3.1 Definition of AI

AI is the generally used term for the science of artificial intelligence which studies the act of making computers perform tasks that originally required human intelligence to be fulfilled. AI extends into various fields of science. Duan et al. (2009) describe it as a compilation of computer science, psychology, philosophy, biology, and various other disciplines. The term “artificial intelligence” originates from a Dartmouth University research project in 1956. Studies conducted during the research project initiated the “Founding period” in research addressing AI. Following the founding period, AI-related literature remained present throughout the end of the 20th century. The first golden age of AI occurred in the late 1970s as advanced expert systems and knowledge engineering influenced the field. The second golden age of AI took place during the 1980s with neural networks functioning as the driving force of development. The third golden age of AI began in 2006 when parallel processing, improved storage capacities and graphics processing units provided a solution to difficulties that the field had previously encountered. Although AI has already been researched during the 20th century, its global breakthrough occurred in 2016 when an AI model “AlphaGo” defeated the world champion in chess. Since this incident, the relevance of AI has experienced rapid growth and attracted global attention from governments, organizations, and academic communities. (Zhang & Lu, 2021).

Zhang & Lu (2021) conducted a study on AI by researching the state of the art and future prospects of the field. The paper highlights big data, algorithms, ML, NLP, hardware, and computer vision (CV) as enabling drivers and technologies in AI. The large volume, variety, and velocity of big data provide AI with an extensive source for learning. (Zhang, 2020) In contrast, algorithms, NLP, CS, and ML function as tools that enable AI to learn from big data by improving recognition rate and accuracy. Algorithms and ML dictate the procedures that take place during the learning process of AI models. NLP, on the other hand, is a key factor regarding communication between AI and humans. NLP refers to a method that enables AI to recognize and understand human language, whereas CV enables machines to recognize and understand an environment through vision similar to humans. Hardware is also considered an enabling driver, as the potential of AI cannot be

released without the efficient parallel computing capabilities of modern hardware (Brynjolfsson & McAfee, 2017).

3.2 Use of AI in DDDM

The introduction of big data has transformed the act of data analysis and altered the concept of DDDM altogether. From an organizational perspective, this considerable change has resulted in various opportunities, but also a diverse number of challenges (See chapter 2.6). AI has provided solutions to several difficulties associated with big data analytics, making it a crucially influential component regarding the DDDM efforts of modern organizations.

Rahmani et al. (2021) conducted a systematic study on AI approaches and mechanisms for big data analytics. Their research highlights AI techniques such as ML, knowledge-based methods, search methods, evolutionary algorithms, decision-making algorithms, and optimization theory as practices that enable improved efficiency, scalability, precision, and privacy in big data analytics. Due to the exponential growth of data generation enabled by IoT and sensor networks, the demand for efficient AI techniques in big data analytics is becoming increasingly more important (Rahmani et al., 2021).

3.2.1 Opportunities

Al-Surmi et al. (2022) researched AI-based decision-making in the context of business organizations by combining IT and marketing strategies to improve operational performance. The study consists of three main phases, and it presents a decision-making framework based on empirical analysis of data collected from 242 managers working in multiple industry sectors. AI techniques utilized in the framework are structural equation modeling (SME) and artificial neural networks (ANN). SME deals with hypothesis testing and combined with an extensive literature review, it is utilized during the first phase of the study to confirm that IT strategies affect marketing strategies. SME is additionally utilized to model relationships between IT- and marketing strategies as well as their impact on operational performance. During the second phase of the study, an ANN model is created based on the examination of data from phase one. The ANN is used to predict how combinations of different IT- and marketing strategies behave and impact the operational performance of an organization. As a result of phase two, the ANN enables the development of a decision-making framework that illustrates the outcomes of

potential strategic decisions. During phase three the ANN is used to simulate all possible strategic combinations and their outcomes. Based on the outcomes, the optimal combination of IT and marketing strategies can be discovered and applied in the organizational environment. The results of the study indicate that operational performance can be improved through the use of AI in strategic decision-making. (Al-Surmi et al., 2022).

Bharadiya (2023) studied the trends and opportunities provided by the use of ML and AI in BI. The study presents predictive analytics and forecasting, AI-powered chatbots and virtual assistants, as well as explainable AI and ethical considerations as considerable trends currently influencing the topic. Predictive analytics and forecasting are enabled by ML algorithms that analyze historical data to identify patterns. By identifying underlying patterns organizations are able to interpret them and predict future events which increases the organization's ability to mitigate risks and optimize operations. The first opportunity highlighted by Bharadiya is automated data analysis and anomaly detection which enhances decision-making and accelerates data analysis. The second opportunity identified by the paper is demand forecasting and dynamic pricing. This opportunity enables organizations to optimize inventory and pricing strategies through predictive analytics. Agile decision-making through AI-driven insights based on real-time data analysis is the third opportunity addressed by the paper. Furthermore, the final opportunity identified in the study addresses enhanced customer experience through personalization. This opportunity utilizes AI-powered analysis of customer data which enables organizations to improve customer engagement and satisfaction through personalization.

3.2.2 Challenges

While Al-Surmi et al. (2022) and Rahmani et al. (2021) examine the opportunities and advantages introduced by AI within big data analytics, Rana et al. (2022) and Figalish et al. (2022) provide a perspective on the risks and disadvantages of utilizing AI in analytics, with a focus on business analytics (BA) and BI. Rana et al. (2022) derive the findings of their research from surveys based on senior and mid-level managers from Indian business organizations varying in size and sector. The study highlights poor data quality, lack of governance, and insufficient training as the main causes of opacity in BA. Due to the

limited understanding of BA, business organizations are prone to encounter drawbacks regarding decision-making, risk management, and operational efficiency.



Figure 3. Vicious circle consisting of key drivers that prevent a successful realization of AI4SABI. (Figalist et al., 2022).

Figalist et al. (2022) researched challenges regarding the use of AI in BI and identified the following six elements (See Figure 3.) to describe the sources of these challenges:

- “Lack of priority, time, and resources,” refers to the insufficient emphasis, interest, and trust that managers and stakeholders have in data-driven initiatives.
- “Low data quality” addresses the difficulties arising from the act of unsuccessfully combining various data sources into effective data analysis, which results in low-quality insights.
- “Inability to cross cultural gap,” refers to the difficulties in communication and differences in expectations between the various stakeholders influencing a data-driven initiative.
- “Ineffective prototypical analysis” deals with the challenge of reaching actual significant results through the creation and maintenance of a continuous and automated data analysis process.

- “Inability to prove value” describes the difficulty of demonstrating the value of data-driven practices to managers, customers, and other stakeholders, especially in the short term.
- “Vicious circle” is the final element proposed by the study. It consists of the five prior elements and describes how they collectively form a cycle that prevents the effective application of AI in data-driven practices.

3.3 AI-powered Dashboards

An AI-powered dashboard refers to a dashboard that incorporates AI technology to enhance the functionality of traditional dashboards. Although scientific literature on AI-powered dashboards is generally limited, researchers have addressed this growing area of research to a certain extent. A significant portion of the current research on AI-powered dashboards studies the concept in the context of healthcare and medicine. Time is an essential factor when it comes to identifying health risks and treating patients, which makes predictive analytics and efficient, high-quality decision-making a valuable asset in the healthcare industry.

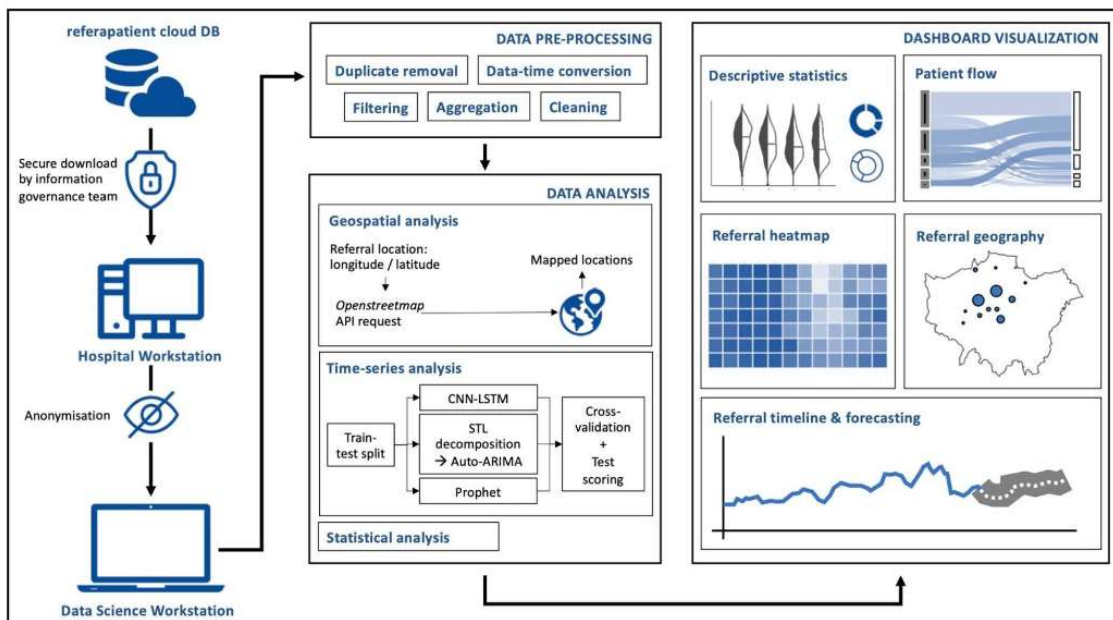


Figure 4. Data acquisition, processing, analysis, and visualization pipeline. (Pandit et al., 2022).

Pandit et al. (2022) researched the analysis of historical and future acute neurosurgical demand by using an AI-powered dashboard. The dashboard utilizes predictive analytics to forecast acute neurosurgical referrals, which enables neurosurgical departments to

prepare for demand and allocate resources accordingly. Three time-series forecasting algorithms were used to analyze input data including 10 033 referrals from a neuroscience center in London. The authors describe these algorithms as follows: “an automated pipeline which combined Seasonal and Trend decomposition using Loess (STL) with an automated regression integrated moving average (Auto-ARIMA) model, a convolutional neural network—long short-term memory (CNN-LSTM) network and Prophet.” The forecasting performance of these algorithms was evaluated through a train-test approach and blocked cross-validation, where the measured forecasting accuracy was based on mean absolute error, root mean squared error, and mean absolute percentage. Figure 4 illustrates the entire development process of an AI-powered dashboard during the study. The process is initiated with a secure download at a hospital workstation performed by the information governance team. This step is followed by the anonymization of the downloaded data before it is transferred to a data science workstation where the pre-processing takes place. Data pre-processing is followed by data analysis which is performed in three phases: geospatial analysis, time-series analysis, and statistical analysis. Finally, the data is transformed into an interactive dashboard which can include visualizations of descriptive statistics, patient flow, referral heatmap, referral geography, referral timeline, and forecasting among various other possibilities depending on the context and the intentions of the user. The research concludes that the effective use of AI-powered dashboards could improve service planning and resource allocation in the healthcare sector, which proceeds to increase the quality of patient care. (Pandit et al., 2022.)

An alternative perspective on the utilization of AI-powered dashboards in the healthcare sector is provided by Tsai et al. (2022), in their article, “Design and Implementation of a Comprehensive AI Dashboard for Real-Time Prediction of Adverse Prognosis of ED Patients”. Based on Chi Mei Medical Centre in China, the article introduces a dashboard that incorporates ML, IoT, and interactive technologies to create prognosis prediction models for eight diseases based on electronic medical records. The objective of the dashboard is to improve decision-making and risk prediction in emergency departments. The dashboard is automatically created and includes comprehensive visualizations illustrating the state of patients in critical condition. The required data is retrieved from the hospital information systems and medical big data warehouses. Once the required data has been retrieved, it is transferred to an AI development platform where ML, deep

learning, and visualization tools process it before transmitting it into an AI web service platform. Once the processed data has reached the AI web service platform, it can be utilized in the development of a dashboard. The user acceptance evaluation included in the study presents high scores regarding the ease of use and perceived usefulness of AI dashboards. Additionally, the results of the study conclude that the utilization of AI dashboards had a positive impact on patient outcomes.

Lughbi et al. (2024) researched the development of a dashboard in the context of cybersecurity. The study introduces an automated dashboard that utilizes NLP to enhance situational awareness and response capabilities against cyber-attacks. The development and functionality of the dashboard are based on social media activity and an NLP model that has been trained with a dataset of 36 071 manually labeled, cyber-attack-related tweets. The model is integrated into a real-time streaming pipeline which allows it to automatically categorize tweets depending on the perceived risk level of the tweet. The dashboard includes geographical maps, bar charts, and data tables among other visualizations to provide details about ongoing cyber-attacks. Users of the dashboard can discover crucial information such as the location and timing of attacks which enables them to evaluate threats and react to them accordingly. The paper proposes that the dashboard enables organizations as well as individuals to discover comprehensive insights about cyberattack patterns which also allows them to prepare for potential future attacks appropriately. The authors propose that the classification accuracy and functionality of the dashboard could be improved through the use of named entity recognition. (Lughbi et al., 2024).

3.4 SAP HANA

SAP High-performance Analytic Appliance (SAP HANA) created by SAP SE, is a multi-model database utilizing in-memory technology, online analytical processing, and online transactional processing to form a comprehensive and efficient database management system (DBMS). The SAP HANA database server can either be implemented in the cloud or on-premises. In addition to storing and retrieving data, the system offers ML-powered analytics as well as advanced search and data integration capabilities for a large number of data types. Organizations can build their own applications or BI functions within the SAP HANA application server, which enables them to derive insights into their business based on real-time data. (SAP, n.d. b). SAP HANA has been extensively adopted to

enhance the DDDM processes and data management capabilities of modern organizations. The widespread use of SAP HANA, coupled with its ability to leverage AI techniques and real-time data, establishes it as a relevant system to examine regarding the use of AI in dashboards.

Färber et al. (2012) provided an architecture overview of the SAP HANA database which discusses the SAP HANA architecture alongside its core components and functionalities. In-memory technology and multi-core central processing units enable SAP HANA to process data rapidly by storing it directly into random access memory instead of traditional disk storage. The memory-based way of operating and a column-oriented storage format are the main architectural elements that enable SAP HANA to perform efficient and optimized data and analytical processing. Additionally, the SAP HANA architecture promotes efficiency in data storage and processing through parallelization and data compression.

Färber et al. (2011) additionally discuss SAP HANA and its functionality in an alternative study: “SAP HANA Database- Data Management for Modern Business Applications”. The paper highlights hybrid data processing engines, advanced query processing, domain-specific language support, integration with modern hardware, and a business function library as the core features of SAP HANA. Hybrid data processing engines enable the DBMS to perform actions on diverse types of data which can be considered an essential requirement in modern enterprise environments. Advanced query processing is performed within SAP HANA’s distributed query processing environment, and it enables the execution of large-scale data operations and complex queries. Queries and other actions in SAP HANA are not limited to the structured query language (SQL) as the language support capabilities of the system allow organizations to perform nuanced data manipulation through domain-specific languages. SAP HANA supports the possibility of integrating modern hardware into the system. By integrating memory capacities, advanced storage technologies, and more efficient processors enterprises can optimize the system’s performance and improve scalability. Finally, the SAP HANA business function library implements business logic into the system which simplifies the system architecture and enhances performance through the execution of business functions within the system’s database engine. (Färber et al., 2011).

3.5 AI-powered dashboards enabled by SAP technologies

The architecture design of SAP HANA allows organizations to connect BI tools, enterprise resource planning software, and custom applications among other features with the system which means that even though dashboards are not directly built-in to SAP HANA, they can be created by utilizing the features of the system. SAP Digital Boardroom (SAP DB) and SAP Analytics Cloud (SAC) are DDDM technologies provided by SAP SE. By combining the features of SAP HANA, SAP DB, and SAC, organizations can create interactive AI-powered dashboards based on real-time data. (Metz, 2021).

SAP DB is a real-time analytics solution that provides a comprehensive overview of an enterprise. It also offers a collaborative environment powered by analytics which makes it a suitable tool for strategic decision-making. SAP DB is mostly used by the top management of an enterprise. The creation of interactive dashboards based on real-time data retrieved from the SAP HANA database is one of its key features. In addition to data provided by SAP HANA, SAP DB is required to utilize the features of SAC to create functional AI-powered dashboards. SAC is a cloud-based analytics tool that can be used for data visualizations, ML-powered analytical processes, and scenario planning. (Metz, 2021), (SAP, n.d. a).

The integration of these three technologies provides a solution that effectively supports the duties of top-level executives through the creation of comprehensive and interactive dashboards. The incorporation of advanced AI-powered analytics and integrated, real-time data enables the functionality of the BI tool. With the support of AI-powered dashboards organizations have an improved ability to make informed, big-picture decisions in dynamic environments. The dashboards could additionally enable the discovery of underlying trends and patterns, thus providing organizations with new, innovative insights.

4 IT Governance

4.1 Definition of IT governance

IT governance, also known as enterprise governance of IT, was defined by the IT Governance Institute (2001) as a concept that consists of the leadership, organizational structures, and processes ensuring that IT sustains and extends the strategy and objectives of an organization.

4.1.1 Purpose and implementation

The ISO/IEC Standard 38500 provides a slightly more recent description of the concept of IT governance and defines it as follows: “The system by which the current and future use of IT is directed and controlled. Corporate governance of IT involves evaluating and directing the use of IT to support the organization and monitoring this use to achieve plans. It includes the strategy and policies for using IT within an organization.” (International Organization for Standardization & International Electrotechnical Commission, 2008). Brown & Grant (2005) researched the element of decision-making in the context of IT governance. Their study states that IT decision rights and IT controls that address the practice of systematically determining the location, distribution, and patterns involved in organizational decision-making responsibilities, are included in the core components of IT governance. The authors additionally address the difference between IT governance and IT management. Their research concludes that IT governance is a broader concept with emphasis on systematic and holistic policies whereas IT management deals with specific IT-related decisions. This indicates that IT management is a segment within the concept of IT governance.

De Haes & Van Grembergen (2004) conducted a study on IT governance and its mechanisms to create an improved understanding of the importance of aligning business and IT in an organizational environment. The paper states that IT governance is a crucial element to consider while attempting to gain a competitive advantage from IT-related solutions. An alternative study on IT governance by Brown & Grant (2005) concurs with this statement by identifying IT governance as a critical factor when it comes to ensuring the cost-effectiveness of IT investments in organizational environments. The study by De Haes & Van Grembergen additionally addresses the practical application of IT governance by identifying influential IT governance frameworks. The responsibility of

top management regarding the implementation and direction of IT governance is also highlighted in the study. IT Infrastructure Library (ITIL) and Control Objectives for Information and Related Technologies (COBIT) are globally utilized IT governance frameworks designed to support the implementation and management of IT governance. The frameworks complement each other, thus functioning effectively within the same environment. COBIT provides information on what needs to be done and ITIL complements it by informing how to do it in practice. The frameworks support the IT governance efforts of an organization by guiding them to emphasize well-defined IT processes with high-level control objectives. Furthermore, the frameworks highlight the importance of appointing distinct roles and responsibilities. The control objectives include maturity models and scorecards that can be utilized to identify the current state of IT governance in an organization as well as its desired state in the future. As a result, organizations can continuously estimate and improve their IT governance practices which could enable them to leverage the benefits of IT-related efforts more effectively. (De Haes & Van Grembergen, 2004).

4.1.2 COBIT 2019

Despite the large number of alternative models, the COBIT framework is often considered as one the most competent solutions regarding IT governance. This study emphasizes the utilization of COBIT due to its comprehensive and detailed perspective regarding IT governance as well as its compatibility with additional competent frameworks such as ITIL and IT4IT.

As a result of the developments in modern technology and general understanding of IT governance during the past two decades, the COBIT framework has regularly been adjusted to fit new contexts. COBIT 2019 is the most recent version of the COBIT framework, and it can be used individually or in combination with other frameworks to provide a holistic and comprehensive framework for IT governance in environments that contain complex and advanced IT infrastructures. “Enterprise Governance of Information Technology: Achieving Alignment and Value in Digital Organizations” by De Haes et al. (2020) provides a comprehensive understanding of IT governance and addresses COBIT 2019 as a focal solution regarding the topic. Studying the COBIT 2019 framework can enable the development of a general understanding regarding the practical appearance of IT governance. The framework identifies 40 objectives that are divided into five domains.

These five domains are further divided into governance objectives and management objectives. (See Figure 5). Governance objectives consist of a group named “EDM” which refers to the evaluating, directing, and monitoring of IT processes. Management objectives, on the other hand, are divided into the following four groups: Align, Plan, and Organize (APO), Build, Acquire, and Implement (BAI), Deliver, Service, and Support (DSS), and lastly, Monitor, Evaluate and Assess (MEA). Governance objectives could be considered as a verification mechanism that ensures the effectiveness and desired influence of management objectives. Management objectives on the other hand focus on concrete performance by addressing operative aspects.



Figure 5. COBIT 2019 Objectives (ISACA, 2018).

A detailed illustration of the governance and management objectives introduced in COBIT 2019 concisely describes each of the 40 objectives included in the framework. The figure provides a comprehensive understanding of focal factors regarding the governance of IT, and it can be observed in the appendices (Appendix 1).

4.2 Adoption of new technology

Tarhini et al. (2015) conducted a critical review of theories and models of technology adoption and acceptance in information system research. Technology adoption has been widely researched for decades, which has resulted in a large quantity of theoretical frameworks. Thus, the authors highlight the importance of choosing a suitable IT adoption model based on the context in which it is utilized. The objective of the study is to reduce the complexity revolving around IT adoption theories by creating a holistic understanding of the most influential IT adoption frameworks. To reach this objective the paper reviews and compares eight focal frameworks on technology adoption by analyzing their key components, development, strengths, weaknesses, and suitability in different contexts. The frameworks addressed by the paper include The Technology Acceptance Model (TAM), The Theory of Reasoned Action, The Theory of Planned Behaviour (TPB), The Unified Theory of Acceptance and Use of Technology, The Diffusion of

Innovation Theory (DOI), Social Cognitive Theory, Motivational Model and the combination of TAM and TPB. The study concludes that all frameworks possess strengths and limitations that influence their suitability in different situations. However, due to the complex nature of modern organizational environments and IT infrastructures, relying on an individual framework is often insufficient. As a result, the paper proposes the possibility of combining multiple technology adoption frameworks to create a suitable solution for each context. Therefore, thorough research on available theoretical frameworks and the unique organizational context in question enables enterprises to effectively utilize technology adoption models even in complex organizational environments. (Tahrini et al., 2015).

Alternatively, “Review on IT adoption: insights from recent technologies” by Gangwar et al. (2013) reviews the academic literature on the adoption of information technology. The paper concurs with the research conducted by Tahrini et al. (2015) and addresses the importance of utilizing models during the adoption of technology in organizational environments. The study highlights TAM and the Technology-Organization-Environment (TOE) framework as prominent options. While both frameworks possess the ability to advance technology adoption individually, the authors propose that combining TAM and TOE into an integrated solution could help organizations understand the variables influencing IT adoption more comprehensively. Thus, the findings presented by Gangwar et al. (2013) and Tahrini et al. (2015) indicate that the integration of multiple frameworks provides a suitable solution for technology adoption in contemporary organizational contexts.

4.2.1 Technology Acceptance Model (TAM) and Technology-Organization-Environment (TOE)

TAM was introduced in 1989 by Fred Davis and it is a focal concept regarding literature on IT adoption. The core components of TAM include Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU refers to the level of effectiveness that a person believes the new IT system, tool, etc. provides them in their work. In other words, if the PU of a new IT system is high, the user believes that it will significantly improve the efficiency of their work. PEOU on the other hand refers to the level of effort a user believes the use of the new IT system requires to be used effectively. This means that if the PEOU of an IT system is high, the user believes it is uncomplicated and easy to use.

If the PU and PEOU of an IT system or tool are high, the users believe that it will improve their work with low effort and are more likely to accept and use it, which results in more successful IT adoption. Alternatively, low rates of PU and PEOU indicate that users believe the new technology will not improve their work but require substantial effort to use. Therefore, an IT system with low PU and PEOU is likely going to be rejected by its users which results in unsuccessful adoption of the system in question. (Marangunić & Granić, 2015).

The TOE framework by Tornatzky and Fleischer introduced in 1990, a year after the introduction of TAM, is an additional foundational IT adoption framework. TOE views the adoption of new technology through three aspects: Technology, organization, and environment. The framework enables organizations to prepare themselves for the adoption of new technology by creating a comprehensive understanding of the adoption process. The creation of this understanding is enabled by detailed consideration of each of the three contexts included in TOE. The technological context addresses the relevant internal and external technologies that an organization uses or might use in the future. This aspect includes considering the advantages and drawbacks of each technology with an emphasis on interoperability, which refers to the compatibility and integration of information systems. By understanding the technological context organizations can ensure that a new system performs well with the existing technology and provides the functionality that is required from it to enable desired outcomes. The organizational context deals with the characteristics and resources of an organization. These characteristics and resources include the size of the organization, managerial structure, degree of centralization, and budgeting among other elements. By identifying these factors organizations can study and address topics such as organizational readiness, top management support, and alignment between the organization's strategic objectives and the new technology. Lastly, the environmental context includes considering how external factors within the organization's environment might impact the adoption of new technology. This includes considering topics such as industry characteristics, regulatory matters, and the state of the economic and competitive environment affecting an organization. In conclusion, studying the organization in these three contexts enables the creation of a comprehensive understanding of the elements influencing the adoption of new IT systems. (Baker, 2012)

4.3 Dashboards as a part of BI and AI adoption

Although the utilization of BI and AI technologies is a standard procedure in modern organizations, inappropriate adoption and utilization processes regarding new IT systems can reduce the success and degree of potential benefits provided by investments involving these technologies. Research on the adoption of BI and AI solutions is a critical factor to consider when attempting to gain a competitive advantage through AI-powered dashboards.

4.3.1 Adoption of BI

Ain et al. (2019) conducted a systematic literature review on BI adoption, utilization, and the success of the efforts in question to discover which factors influence the ability or inability of an organization in leveraging the potential benefits of BI technologies. To fulfill this objective the study reviews 111 peer-reviewed articles addressing the adoption, utilization, or success of BI technologies between 2000 and 2019.

The research recognizes the importance of theoretical adoption and utilization frameworks and addresses the influence and usage of frequently used theories such as DeLone & McLean's IS success model, TAM, DOI, and TOE. In addition to the theoretical frameworks, the research highlights various organizational and technological factors that influence the adoption, utilization, and success of BI technologies in an organizational context. Significant organizational factors discovered by the authors include management support, organizational culture, and change management. The support of top management ensures the prioritization of BI initiatives and an appropriate allocation of resources such as financial support and time. Organizational culture on the other hand refers to the qualities of an organization. An enterprise with a suitable organizational culture regarding the use of BI technologies operates in a data-driven manner and continuously encourages its employees to become more efficient by providing opportunities regarding the use of BI tools. Effective change management decreases resistance and supports employees in a new environment through training and communication. Technological factors addressed in the paper deal with the quality of systems and information as well as the IT infrastructure of an enterprise. System quality refers to aspects within the BI system and includes elements such as ease of use, usefulness, and user satisfaction whereas information quality refers to the accuracy,

consistency, and timeliness of the data utilized by the system. IT infrastructure is closely related to information and system quality, and it ensures that data is accessible and integrated throughout an organization. (Ain et al. 2019)

Van Hillegersberg & Koenen (2016) studied the adoption of BI from the perspective of group decision support systems (GDSS). The study is based on interviews conducted with frequent, infrequent, and former users of GDSS as well as non-users. The authors utilize a collaboration technology adoption framework to discover why web-based GDSS have not been widely implemented into organizational contexts. The framework divides deployment and adoption into two groups that include various elements. The first group “Fit” describes how well a technology solution matches the workflows and processes of an organization. The second group “Viability” includes elements regarding the economic, organizational, and technical factors influencing the context. The paper proposes organizational resistance to change, financial concerns, issues with interoperability, lack of technical capabilities among employees, and cultural difficulties as possible reasons for the low success of web-based GDSS. The research also suggests that despite these challenges, a successful adoption process could be enabled by a facilitator with the capability to consider the highlighted difficulties while creating a plan for the adoption. (Van Hillegersberg & Koenen 2016).

4.3.2 Adoption of AI

Chatterjee et al. (2021) research AI adoption in the context of manufacturing and production firms. The authors utilize an integrated TAM-TOE model to study the phenomenon and discover focal factors influencing AI adoption. The study is based on data from 340 employees gathered across multiple organizations utilizing modern technologies. The findings introduce organizational and technological factors such as organizational readiness, leadership support, system interoperability, PEOU, and PU to be included among the most significant factors influencing AI adoption. Thus, the factors influencing the adoption of AI and BI align closely, as Ain et al. (2019) highlight corresponding factors in their paper regarding the adoption of BI.

An alternative paper on the factors influencing the adoption of AI by Alsheibani et al. (2018) examines AI readiness at the firm level by utilizing the TOE and DOI frameworks. The paper proposes an integrated model (See Figure 7.) which suggests that AI adoption is influenced by AI readiness. AI readiness consists of technological readiness,

organizational readiness, and environmental readiness. Technological readiness includes relative advantage compatibility. Relative advantage refers to the comparison of potential AI solutions by evaluating the benefits they provide. Compatibility refers to the compatibility between an AI technology and the business strategies of the adopting organization. Organizational readiness includes factors addressing top management support and the size and resources of the organization. Lastly, environmental readiness addresses external factors influencing the adoption of AI and includes competitive pressure and government regulatory issues. Similar to the study conducted by Chatterjee et al. (2021), the findings by Alsheibani et al. (2018) indicate that scientific literature on the adoption of AI and BI share various aspects.

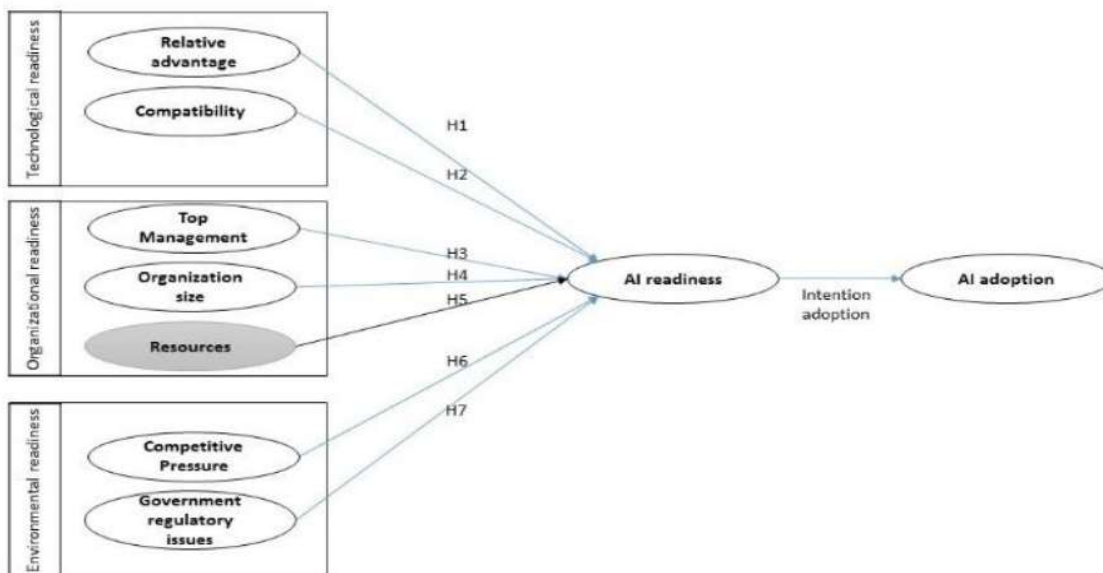


Figure 6. Research framework for AI adoption at firm level (Adapted from the TOE framework) (Alsheibani et al., 2018).

4.4 Governance of BI

The need for robust BI governance has emerged as a result of BI technology becoming a strategically essential element in organizational environments. Wixom & Watson (2010) discuss the role of BI in modern organizations and address the importance of governance processes regarding the use of BI technologies. The authors suggest that based on three case studies, the effective governance of BI enables organizations to increase the benefits provided by these technologies. To achieve this improvement, the paper proposes that the governance of BI should consist of enterprise-wide control functions that measure the utilization and influence of BI technologies. These control functions include the

alignment of BI solutions and business strategy, the management of data quality and consistency as well as the prioritization of projects. The research further explores the importance of data integration and the promotion of data-driven methods within organizations attempting to leverage the potential benefits enabled by BI technologies. (Wixom & Watson, 2010.)

A study on BI governance by Chugh & Grandhi (2013) addresses the significance of BI as well as the integration of its governance with corporate governance. The paper concurs with the alternative research on BI by Wixom & Watson (2010) and recognizes the growing importance of BI and its governance. However, the research by Chugh & Grandhi includes a stronger emphasis on the governance aspect. The authors identify common challenges regarding the implementation of BI technologies and aim to provide a solution to these difficulties by proposing models for the development of a BI governance framework and for the alignment of BI governance and corporate governance.

The BI governance framework consists of four phases. Phase one, “Conceptualise” includes assessing the BI needs of an organization and identifying a solution to these needs. It is followed by phase two, “Plan” which addresses the alignment of organizational elements and the new technology as well as assigning roles and responsibilities to employees regarding the process. Phase three, “Execute” deals with data-related matters such as data quality, accessibility, and security. The final phase “Audit” ensures that the new technology is effective, and it includes measuring and analyzing the effect of the new BI system. (Chugh & Grandhi, 2013).

The research by Chugh & Grandhi proposes that in order to ensure the alignment of BI and strategic objectives, BI governance should not exist in isolation. Therefore, the second model (See Figure 8.) proposed by the authors describes how BI governance could be integrated into corporate governance. The model includes two main entities “Corporate Governance” and “BI Governance”. These entities interact with each other to enable successful governance of BI systems. Corporate governance includes the following four elements: “Strategic Goals,” “Accountability & Responsibility,” “Performance” and “Regulate & Control.” These elements enable Corporate Governance to provide BI governance with feedback that guides BI in its efforts to support organizational and strategic objectives. BI Governance includes “Tactical Initiatives,” “Business Functions,” “Data Organisation” and “IT Systems.” These elements enable the functionality of BI

systems and allow BI Governance to institutionalize the outcomes of BI usage in Corporate Governance. Corporate Governance proceeds to estimate the outcomes of BI usage from the perspective of strategic objectives and provides BI Governance with feedback based on the estimations. (Chugh & Grandhi, 2013.)

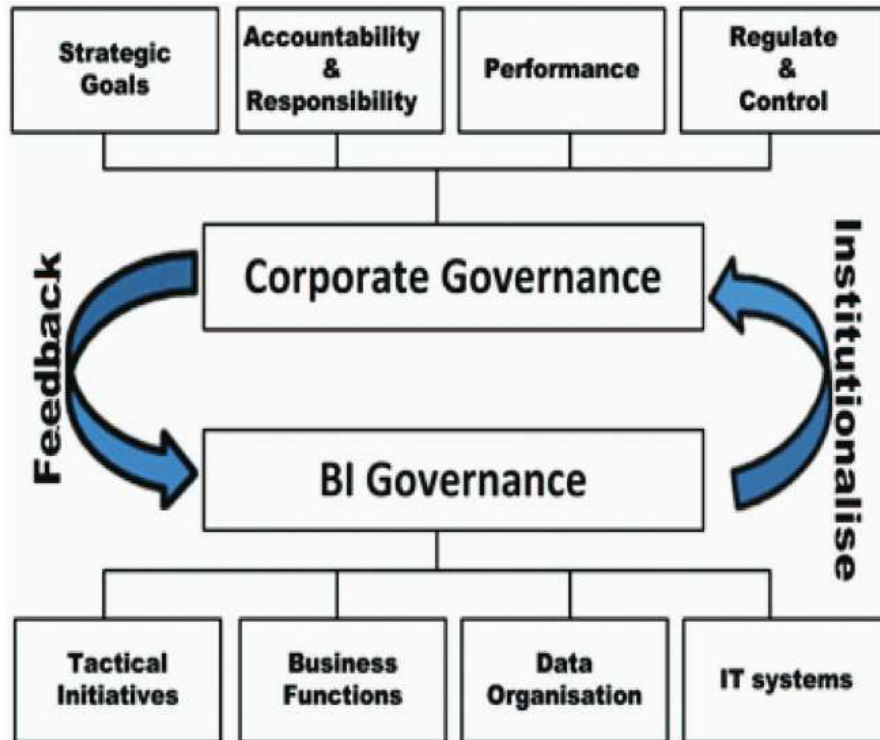


Figure 7. Model for aligning BI governance framework with corporate governance framework (Chugh & Grandhi, 2013).

4.5 Governance of AI

Similar to the governance of BI, the significance of governing the AI efforts of an organization has become an integral part of corporate governance. Mitigating risks regarding information security, privacy, and accuracy are among the top priorities of AI governance. (Witt et al., 2021). As a result of the rapid technological developments regarding AI, the concept of AI governance is relatively new. Dafoe (2018) provides a comprehensive research agenda for AI governance that applies to organizations but also exceeds organizational boundaries. The research agenda identifies three significant research areas: The technical landscape of AI, politics revolving around AI, and ideal AI governance envisions. The author divides his research into these three segments to address how possible risks and opportunities related to AI could be managed through AI governance.

The research by Dafoe suggests that research on the technical landscape of AI should focus on capabilities, limitations, and future possibilities regarding the technical developments in AI. By researching these matters AI governance can be implemented into the concurrent technological environment however, it is also prepared for potential future alterations regarding the development of AI. The second area of research focuses on AI politics. According to the study, it should address the influence that political implications have on AI by addressing the relationships between AI and different actors such as governments, corporations, and other figures possessing authority or power. The third area of research focuses on envisioning ideal structures, processes, and policies that ensure the inclusion of ethical principles in AI governance. By incorporating ethical principles and creating governance institutions as well as control mechanisms in AI governance, the probability of security breaches and inequality decreases. These holistic rules for AI governance identified by Dafoe, could be considered as the foundation of AI governance despite its limited emphasis on organizational environments.

Taeihagh (2021) studied the governance of AI through research on its challenges and necessities. The study emphasizes how scientific research lacks research on AI governance despite the significant influence it has on the safety and well-being of individuals and organizations. To remove this gap in scientific literature, the author addresses various AI governance approaches that enable organizations and authorities to mitigate risks and harness benefits regarding AI and its use.

The study by Taeihagh (2021) initially identifies various challenges and continues by presenting potential solutions. The rapid development of AI technologies is one of the focal challenges identified by the author. Because of the rapid and continuous changes in AI, it is difficult to create governance structures and policies that manage to keep up with the fast-paced developments. Another integral challenge arises from the complex and unpredictable nature of AI technologies. AI systems that behave unexpectedly and lack transparency are challenging to govern because their nature and behavior often cannot be completely understood in advance or even afterward in some cases. To manage these challenges, the research proposes various solutions and approaches that could be implemented into AI governance practices. According to the research international cooperation and integration of multiple frameworks with different perspectives is one of the most essential elements in the development of effective AI governance solutions. A significant attribute of an appropriate AI governance solution includes flexible structures

and policies created through the extensive incorporation of various relevant stakeholders. Flexibility enables the governance of AI to perform rapid adjustments based on new developments regarding AI technologies. Additionally, the use of transparent AI technologies and the involvement of ethical principles is critical. Transparent AI systems combined with the extensive incorporation of relevant stakeholders provide AI governance with various perspectives which relieve the challenges posed by the unpredictable nature of AI. (Taeihagh, 2021).

Mäntymäki et al. (2022) provide a comprehensive framework for the governance of AI in an organizational context. “The Hourglass Model of Organizational AI Governance” promotes the inclusion of ethical principles in the use of AI and provides support for the alignment of AI processes and regulatory requirements. To enable this, the model systematically addresses AI governance at organizational, environmental, and AI system layers. Figure 8 illustrates the components of the model and additionally demonstrates how distinct layers interact with each other.

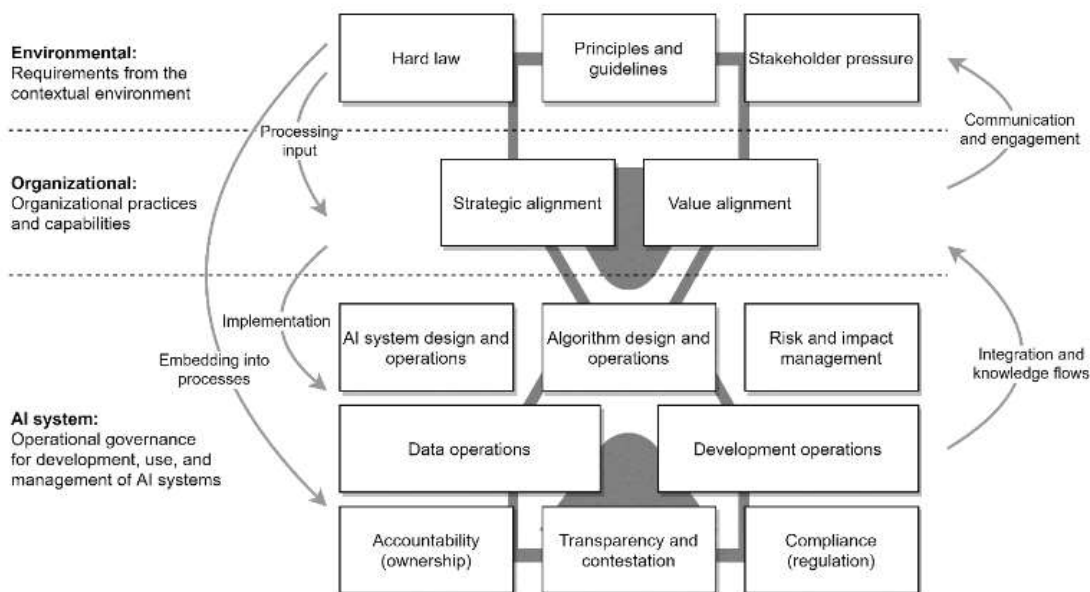


Figure 8. The hourglass model of organizational AI governance (Mäntymäki et al., 2022)

The environmental layer addresses requirements from the contextual environment and includes government regulations, ethical guidelines, and societal expectations, whereas the organizational layer addresses organizational practices and capabilities through strategic alignment, risk management, and the development of governance policies. The model has an emphasis on the AI system layer as it includes eight distinct components:

1. AI system, 2. algorithms, 3. data operations, 4. risk and impacts, 5. transparency, explainability, and contestability, 6. accountability and ownership, 7. development and operations and 8. compliance. Detailed governance components and tasks have been formulated for each of the eight components (Appendix 2), which enables organizations to ensure that their AI governance function appropriately addresses the external and internal requirements derived from the contextual environmental and organizational layers. (Mäntymäki et al., 2022).

4.5.1 ISACA and COBIT

COBIT 2019 is one of the leading IT governance frameworks (See Chapter 4.1) supporting the IT governance efforts of modern organizations. The framework does not directly address AI governance, however, the Information Systems Audit and Control Association (ISACA), the organization responsible for creating COBIT 2019 suggests that the COBIT 2019 framework can either be adjusted for AI governance or used as it is, to a limited extent.

Reis et al. (2024) address AI governance and risks associated with it through COBIT 2019 from the perspective of top management in their article on the ISACA Now Blog. The article emphasizes that executives are responsible for considering the ethical implications of AI and the strategic directions of the organization while creating the methods used to govern AI in an enterprise. Additionally, Reis et al. emphasize the creation of AI governance policies that ensure the involvement of legal and regulatory considerations when it comes to utilizing AI technologies. The authors identify seven risks to be considered by executives regarding the use of AI. These risks include reputational risks caused by the misuse of AI, regulatory risks resulting from failure to adhere to data regulations and AI norms, risks regarding financial stability caused by large investments, risks regarding strategic misalignment between the use of AI and business strategy, risks arising from cybersecurity and data privacy, risks associated with ethical and social responsibility and finally, risks affecting the workforce of an enterprise. To manage these risks, the authors propose a tailored approach to the COBIT 2019 framework, (Appendix 3) which includes governance and management objectives that have been adjusted to provide a solution for managing AI threats and risks from the perspective of directors. (Reis et al., ISACA, 2024).

Ramachandran (2024) provides an alternative article on AI governance on the ISACA Now Blog and addresses key steps to successfully govern AI with the support of an AI risk management framework designed by the National Institution of Standards and Technology (NIST). The author states that the amount of scientific literature addressing AI governance has significantly increased in recent years, which indicates that the lack of research in 2021 addressed by Taeihagh (2021) does not reflect the current state of literature regarding AI governance. Despite the large amount of available material, the absence of a distinguished and widely deployed framework hampers the ability of individual enterprises to design effective AI governance solutions. To address this challenge, the article proposes a guide consisting of six key steps to guide organizations in their efforts to govern the use of AI. Step 1 promotes the inclusion of NIST's seven characteristics of AI trustworthiness in AI governance risk metrics. NIST's seven characteristics describe a trustworthy AI followingly: Valid and reliable, safe, secure, resilient, accountable and transparent, explainable and interpretable, privacy-enhanced and fair, with harmful bias managed. Step 2 instructs enterprises to value the seven characteristics either quantitatively or qualitatively with a preference for a quantitative approach. Step 3 emphasizes the importance of multi-disciplinary perspectives through the inclusion of various internal and external stakeholders. Step 4 promotes the use of NIST's AI Risk Management Framework Core (AI RMF). The AI RMF addresses AI governance through three functions: Map, Measure, and Manage. "Map" refers to the efforts taken to understand the context and risks associated with it. "Measure" on the other hand refers to the analysis and assessment of identified risks. Lastly, "Manage" includes the actions taken to deal with the identified risks based on their severity derived from the analysis and assessment. Step 5 states that the guidelines are not indisputable, and they should always be considered depending on the nature of the context. Step 6 completes the guide by stating that the principles of financial and internal audit do not apply in the context of AI audit. Instead, AI audit should be performed with the principles of management audit or social audit. To conclude the article, Ramachandran suggests that the integration of multiple frameworks possessing alternative perspectives could provide the most optimal solution for AI governance in current circumstances. (Ramachandran, 2024).

5 Findings

5.1 Overview

The findings of this study were discovered through a literature review on AI-powered dashboards and integral topics influencing the concept. They have been organized into three segments to provide explicit answers regarding the current state of best practice dashboards as well as their adoption and governance. The overview provides summarized answers to each of the three research questions whereas, the sequent subchapters introduce the findings in more detail.

1. RQ 1: “What are the current best practices for dashboards, and do they utilize AI?”

Current dashboard best practices are interactive and versatile BI tools that provide value to organizations by improving operational efficiency and decision-making through illustrative visualizations and efficient data analysis. The utilization of AI techniques in dashboard development is not uncommon; however, the phenomenon is relatively new and awaits further research. Existing literature recognizes the potential of AI in the context of dashboards and highlights it as an important research direction. Thus, the relevance of AI-powered dashboards is likely to continue its growth.

RQ 2: “If AI is utilized, how does it affect the adoption of dashboards from the perspective of executives?”

Research identifies the selection of an appropriate adoption framework as a critical factor influencing the adoption of new technology. Literature on technology adoption includes a large variety of competent frameworks that emphasize different factors influencing adoption processes in various contexts. Due to this extensive collection of frameworks, an appropriate solution to the adoption of AI and BI-related technologies can be determined in most situations. A suitable solution can either consist of an individual framework or the use of an integrated framework utilizing a combination of models. The solution can be determined through research on the organizational context, the technology that is being implemented, and the collection of available frameworks. Thorough research on organizational, technological, and environmental factors enables an organization to understand its unique context and potential capability of adopting new technologies. As

a result, the organization can reflect available adoption frameworks in its context to determine a suitable solution to support the adoption process of AI-powered dashboards.

RQ 3: “How does the potential utilization of AI affect the governance of dashboards?”

While the importance of BI governance has been apparent for several years, the concept of AI governance has recently emerged due to technological developments in AI and the global deployment of AI technologies in organizational environments. Literature on IT governance and BI governance is extensive and includes various frameworks. However, literature on AI governance does not recognize any distinguished and extensively implemented frameworks, despite the large amount of research that has recently been conducted regarding the concept. As a result, organizational functions governing the use of IT are experiencing difficulties with identifying an appropriate solution to manage the unpredictable, and occasionally unexplainable nature of AI.

The use of AI in dashboards necessitates organizations to view IT governance from the perspective of BI governance and especially AI governance. Research recognizes appropriately adjusted IT governance frameworks and the integration of multiple AI governance frameworks as suitable solutions for the difficulties arising from the absence of a distinguished and comprehensive AI governance framework. AI technologies introduce significant challenges and risks regarding the security, transparency, and accuracy of data. Literature suggests that in order to mitigate these risks, organizations are required to construct flexible and diverse governance structures promoting the use of transparent AI technologies. Flexibility enables AI governance to react accordingly to rapid technological developments whereas diversity enabled by extensive stakeholder incorporation mitigates risks regarding unpredictability.

5.2 Current dashboard best practices

The first research question of this study addresses the current state of dashboards and the role of AI regarding their functionality. The answer to this research question is addressed through findings related to the development and utilization of dashboards, the current state and utilization of AI-powered dashboards, as well as a tangible method that enables the development of AI-powered dashboards in modern organizations.

RQ 1: “What are the current best practices for dashboards, and do they utilize AI?”

Dashboards are widely used BI tools that aid users in interpreting complex situations by collecting, summarizing, and understandably presenting relevant data. Modern dashboards influence organizations on strategic, tactical, and operational levels through data-driven methods that produce various benefits such as improved decision-making and increased operational efficiency. Dashboards improve decision-making by simplifying situations through visualizations whereas operational performance is being promoted through accelerated operations enabled by efficient data analysis and automatization. The use of dashboards often occurs within the environment of a broader BI system that consists of multiple tools. However, dashboards can also be utilized individually.

Best practice dashboards are interactive and versatile, which allows them to provide support in a variety of different contexts. The ability to serve multiple purposes is enabled by the tailoring of dashboards. This can be performed through user-based customization, system-based personalization, or adaptation performed by the dashboard itself. Researchers have created general guidelines to support the development of dashboards, however, current research does not include a comprehensive framework that could be applied to any specific context. This means that existing frameworks are required to be adjusted based on the intended purpose of dashboards in specific organizational environments.

Scientific literature demonstrates that state-of-the-art dashboards utilize various AI techniques. Although research on AI-powered dashboards is currently limited and in its early stages, the existing literature indicates that the area of research will likely be studied further and remain relevant in the future. Vázquez-Ingelmo et al. (2019) identified AI-powered dashboards as a significant direction for future research regarding dashboards and their customization. Additionally, challenges regarding the utilization of big data in dashboards will likely encourage researchers to conduct further studies on the relationship between AI and dashboards, as AI methods have been identified as a prominent solution when it comes to managing and analyzing big data.

Studies conducted by Panidt et al. (2022) and Tsai et al. (2022) demonstrate the state of existing literature regarding the practical use of AI-powered dashboards (See chapter 3.3). Both studies research the role of AI as a key element in the functionality of dashboards utilized in the context of healthcare. Alternatively, Lughbi et al. (2024) studied the concept from the perspective of cyber-attacks.

A significant amount of existing research on AI-powered dashboards focuses on utilizing the technology within the healthcare sector. Efficient and appropriately reasoned decision-making is essential in dynamic environments such as emergency departments. As demonstrated in research by Tsai et al. (2022), the implementation of AI-enabled real-time predictions in dashboards enables employees working in emergency departments to make well-informed decisions faster than before. As a result, the quality of treatment for patients in critical condition improves. The real-time predictions displayed by the dashboards have been created through the utilization of ML techniques on patient data that has been gathered by IoT devices. An alternative study in the context of health care by Pandit et al. (2022) utilizes time-series forecasting methods to create dashboards that predict acute neurosurgical demand. According to the study, the implementation of these AI-powered dashboards provides hospitals with an improved ability to plan services and allocate resources accordingly. Studies indicate that the potential impact of utilizing AI in the context of health care is considerable, which explains the high frequency of studies focusing on this specific field. The AI-powered dashboards addressed by Lughbi et al. (2024) utilize NLP to improve situational awareness and response capabilities against cyber-crime. The NLP model included in the study automatically classifies tweets based on their perceived risk level. As a result, users of the dashboard possess an improved ability to identify potential risks regarding cyber-attacks.

Contrary to the previously addressed AI-powered dashboards that serve a specific purpose, SAP SE provides a comprehensive method for the creation of AI-powered dashboards in the context of executive decision-making. This solution is enabled by the combined utilization of the SAP HANA database, SAP Analytics Cloud (SAC), and SAP Digital Boardroom (SAP DB). SAP HANA is a multi-model database that enables the utilization of real-time data, whereas SAC is a cloud-based analytics tool that utilizes ML in analytical processes. SAP DB is a real-time analytics solution designed for the executives of an organization. It provides a comprehensive overview of the enterprise and enables the creation of AI-powered dashboards by utilizing the analytical capabilities of SAC and data retrieved from the SAP HANA database. AI-powered dashboards created in SAP DB improve and accelerate the strategic decision-making capabilities of top management by utilizing ML techniques that enable the discovery of underlying patterns.

The literature describes modern dashboards as versatile BI tools that support organizations in their data-driven efforts by improving decision-making processes and

simplifying complex situations through visualizations, data analysis, and automatization. Based on scientific research addressing the use of AI in dashboard technology, it can be concluded that state-of-the-art dashboards utilize AI in various ways to benefit users and improve the functionality of traditional dashboards. Technologies provided by SAP were addressed in this thesis to demonstrate a practical and feasible method to create AI-powered dashboards that support decision-making on the level of top management. Based on the findings related to the use of SAP HANA, SAC, and SAP DB, it can be concluded that through the utilization of appropriate modern technology, the development of AI-powered dashboards is generally possible in the context of executive decision-making.

5.3 Adoption of AI-powered dashboards

Findings related to the adoption of AI-powered dashboards are introduced in this subchapter to address the second research question. The adoption of AI-powered dashboards is addressed through findings derived from the examination of literature on technology adoption, with an emphasis on BI and AI adoption.

RQ 2: “If AI is utilized, how does it affect the adoption of dashboards from the perspective of executives?”

To ensure the successful adoption of AI-powered dashboards in an organizational context, the creation of an appropriate adoption process is essential. The scientific literature on the adoption of new technology provides a general foundation for the creation of this process however, perspectives from literature addressing the adoption of BI and AI should also be considered to enable the creation of an accurate and context-specific adoption process.

Research on technology adoption has been conducted for decades which has resulted in a broad supply of theoretical frameworks that have been developed to guide organizations in their efforts to adopt new technologies. Prominent and widely accepted technology adoption frameworks include The Technology Acceptance Model (TAM), The Theory of Reasoned Action, the Technology-Organization-Environment (TOE), The Theory of Planned Behaviour, The Unified Theory of Acceptance and Use of Technology, The Diffusion of Innovation Theory (DOI) and The Social Cognitive Theory, however, a large number of alternative competent frameworks also exist.

Although the available theoretical frameworks include similar features, the main focus often differs between adoption models. For instance, TAM addresses technology adoption

by measuring perceived usefulness (PU) and perceived ease of use (PEOU). High values of PU and PEOU indicate that the adoption process is likely to succeed. TOE on the other hand guides the adoption process by instructing organizations to view it through factors influencing the technological, organizational, and environmental contexts of an organization. Due to the large number of potential solutions emphasizing various elements, studies highlight the importance of determining a suitable framework based on the organizational context occurring in specific circumstances. Furthermore, relevant literature highlights the possibility of forming a suitable solution by combining multiple frameworks into an integrated model. In conclusion, thorough research on the internal and external environments of an organization, combined with a comprehensive understanding of available theoretical frameworks increase the probability of identifying a suitable solution to support the adoption of new technology in an enterprise.

BI adoption as well as AI adoption can be considered as segments within the more general concept of technology adoption. Because of this, literature on the three areas of research closely align and mainly addresses the same frameworks and elements. From the perspective of AI-powered dashboards, literature on the adoption of BI and AI is also significant as it highlights specific factors excluded in the literature examining technology adoption in general.

Research on the adoption of BI and AI addresses various theoretical frameworks including TAM, DOI, and TOE. Studies suggest that general technology adoption frameworks can be adjusted and combined to provide suitable solutions for the adoption of BI and AI technologies. Literature on both concepts addresses the importance of researching organizational and technological factors that influence the adoption of BI and AI.

A systematic literature review on BI adoption by Ain et al. (2019) identifies management support, prioritization of BI initiatives, appropriate resource allocation, and an organizational culture that promotes a data-driven way of operating, as significant organizational factors influencing the adoption of BI investments. Alternatively, technical factors impacting BI adoption include system quality and information quality as well as a functional and interoperable IT infrastructure.

Organizational factors influencing AI adoption identified by Alsheibani et al. (2018) include the size and resources of an organization as well as top management support.

Technological factors on the other hand include interoperability between systems and consideration regarding the relative advantages of a potential AI solution in comparison with other solutions. The authors utilized the TOE and DOI frameworks to identify AI readiness as the main element influencing AI adoption. In addition to organizational and technological factors, the research suggests that environmental factors significantly influence AI adoption through AI readiness. Environmental factors include regulatory and competitive matters among other external elements that have an impact on the environment of an enterprise.

In conclusion, the literature on BI and AI adoption mainly agrees on the elements that influence an adoption process. Certain differences exist between the two concepts however, regarding the adoption of AI-powered dashboards a suitable solution can be identified by adjusting a technology adoption framework with specific perspectives derived from literature on BI and AI adoption.

5.4 Governance of AI-powered dashboards

Findings related to the governance of IT, BI, and AI are addressed in this section to provide an answer to the third research question of the study. This includes addressing prominent IT governance frameworks as well as their features related to the governance of AI and BI.

RQ 3: “How does the potential utilization of AI affect the governance of dashboards?”

IT governance performs the development and maintenance of structures, processes, and policies directing and controlling the use of IT in an organization. Therefore, the governance of AI-powered dashboards is included within this function. As with IT adoption, scientific literature on IT governance emphasizes the importance of utilizing frameworks to ensure the function performs its responsibilities appropriately. The COBIT framework by ISACA is a renowned framework, widely recognized in scientific research addressing IT governance. The COBIT framework has existed since 1996 and it has frequently been adjusted to provide a timely and comprehensive model to support IT governance. The most recent model, COBIT 2019 guides the IT governance efforts of an enterprise through 40 governance and management objectives that address and control significant elements influencing the use of IT in organizational contexts.

In addition to IT governance, this thesis studies the more specific topics of BI governance and AI governance to suggest an appropriate solution for the governance of AI-powered dashboards. Research by Wixom & Watson (2010) suggests the implementation of enterprise-wide control functions that measure the effectiveness of BI technologies by ensuring an appropriate level of data management, and project prioritization as well as the alignment of BI and business strategy. Chugh & Grandhi (2013) alternatively propose a BI governance framework with four phases. The framework includes: 1. Conceptualizing the BI needs of an organization and identifying a suitable solution 2. Planning the alignment of organizational elements and new technology, 3. Executing the deployment while ensuring the maintenance of an appropriate level of data quality, accessibility, and security, and 4. Auditing the effectiveness of new technology through measurements and analysis. The research by Chugh & Grandhi (2013) additionally identifies the importance of integrating BI governance into corporate governance and proposes a model that demonstrates the functionality of this integrated governance function. The “Model for aligning BI governance framework with corporate governance framework” presented in the research illustrates how BI governance functions more effectively in close interaction with corporate governance. This interaction includes BI governance institutionalizing the effect of BI technology on corporate governance, which is followed by corporate governance providing feedback to BI governance based on the performance of BI technology from the perspective of business strategy. The continuous repetition of this rotary interaction improves BI governance and ensures the alignment of BI and business strategy.

As a result of rapid technological developments in AI during recent years, a large amount of research has already been conducted on the concept of AI governance, despite its recent emergence in scientific literature. AI governance aims to direct and control the use of AI by mitigating risks regarding the security, privacy, and accuracy of information. A comprehensive research agenda by Dafoe (2018) identifies the technical landscape of AI, AI politics, and ideal AI governance envisions as the most significant research directions. Research on the technical landscape and politics of AI identifies risks and opportunities regarding the use of AI, whereas research on ideal AI governance envisions addresses the actual structures, processes, and policies enabling the governance of AI to deal with the identified risks and opportunities. Research on the challenges of AI governance by Taeihagh (2021) identifies the continuous and rapid development of AI coupled with its

complex and unpredictable nature as significant challenges influencing the concept. Continuous technological developments altering AI prevent the creation of permanent governance structures and policies. Furthermore, the behavior of complex AI technologies lacking transparency, is difficult to comprehend, which hampers the effectiveness of AI governance in organizations. To deal with these challenges, the study proposes the promotion of transparent AI technologies and the creation of flexible AI governance structures through extensive stakeholder incorporation. These solutions improve AI governance by providing organizations with an enhanced understanding of AI technology as well as a more reactive and versatile collection of governance structures.

Mäntymäki et al. (2022) provide a comprehensive framework addressing AI governance. “The Hourglass Model of Organizational AI Governance” views AI governance through three layers describing the contextual external and internal environments of an organization with an emphasis on its AI systems. The model aligns with recent AI-related regulatory requirements in the EU and promotes the integration of ethical principles in AI governance. The complexity and uncertainty regarding the potential implementation of the model are reduced through the inclusion of detailed descriptions addressing the components and tasks included in the model.

The COBIT 2019 framework does not directly address the governance of AI, however, ISACA suggests that it can be adjusted to support AI governance. Reis et al. (2024) identify seven risks related to AI governance from the perspective of top management. These risks include reputational risks, regulatory risks, financial risks, strategic risks, security risks, ethical and social risks, and finally, workforce-related risks. To mitigate them, the authors propose a tailored approach to the COBIT 2019 framework which includes governance and management objectives adjusted to the context of AI governance. Ramachandran (2024) provides a solution to deal with the absence of a distinguished, comprehensive AI governance framework. The author recognizes the integration of multiple frameworks as an appropriate solution for AI governance and proposes a guide that addresses AI governance through six key steps. The guide utilizes the National Institution of Standards and Technology’s (NIST) seven characteristics of AI trustworthiness, as well as NIST’s AI Risk Management Framework Core (AI RMF). According to NIST, a trustworthy AI is valid and reliable, safe, secure, resilient, accountable, transparent, explainable, interpretable, privacy-enhanced, and fair, with harmful bias managed. The first two steps of the guide instruct organizations to create

and quantitatively measure AI governance risk metrics that are based on the seven characteristics of AI trustworthiness. Step 3 emphasizes the incorporation of various internal and external stakeholders in AI governance. Step 4 promotes the use of AI RMF which instructs organizations to understand their unique context and risks associated with it. Furthermore, this step includes the analysis and assessment of the identified risks as well as the determining of concrete actions to manage them. Step 5 states that the guide should be followed depending on the context as it is not indisputable and lastly, step 6 instructs organizations to treat AI governance by using the principles of management audit and social audit, instead of the principles of financial audit and internal audit.

In conclusion, IT governance is the organizational function that controls and directs the use of IT in an enterprise. AI governance is a relatively new element within the concept of IT governance and its purpose is to mitigate risks stemming from the unpredictable and complex nature of AI technologies. To govern the use of AI-powered dashboards, organizations are required to adjust their IT governance efforts from the perspective of BI governance and AI governance. However, difficulties arise due to the absence of a distinguished, comprehensive AI governance framework recognized by scientific literature. This necessitates organizations to either adjust IT governance frameworks into the context of AI governance or combine multiple AI governance frameworks into an integrated solution.

6 Discussion

6.1 Interpretation of findings

Findings presented in Chapter 5 indicate that the incorporation of AI technologies is perceptible in modern dashboard development. The utilization of AI enhances dashboard capabilities such as data processing, visualization, and personalization which enables organizations to improve the efficiency and effectiveness of their DDDM efforts. These benefits could be leveraged effectively, especially in the context of executive-level decision-making. This assumption is based on the ability of dashboards to simplify complex situations, which is a substantial benefit regarding the duties of the executives of an organization. SAP technologies provide a practical method to develop AI-powered dashboards in the context of executive-level decision-making. This could be considered as an additional indication of the compatibility between executive-level decision-making and AI-powered dashboards. The findings addressing dashboards additionally identify AI as an integral element regarding future research on dashboards. Based on the scientific perception of AI's role in dashboard development and the potential organizational benefits enabled by AI-powered dashboards, it is probable that the relevance of this data-driven method will continue increasing.

The importance of utilizing theoretical frameworks to support the adoption of new technology in organizational environments is emphasized in the findings of this study. Modern enterprises possess unique organizational contexts and technological infrastructures which has resulted in an extensive collection of theoretical adoption frameworks. These frameworks emphasize a variety of factors influencing technology adoption, which necessitates organizations to thoroughly research their individual context as well as the collection of available frameworks. To enable a successful adoption of AI-powered dashboards in an organization, this study suggests the appointment of a competent employee or project team to design, implement, and control the adoption process, based on extensive research addressing the organizational context, potential technology solutions, and available adoption frameworks. The top management of an organization could provide an optimal context for the initial attempts to adopt AI-powered dashboards in an organizational environment. This assumption is supported by the inclusion of mainly motivated and competent users, as well as the small size of the adoption group. These factors could also positively influence the governance of AI-

powered dashboards. Additionally, various factors negatively influencing the adoption of AI and BI technologies are directly related to the top management of an organization. These factors include top management support, project prioritization, organizational resistance to change, and resource allocation. By deploying AI-powered dashboards in the context of top management, these difficulties are less likely to prevent the adoption process from succeeding.

Once AI-powered dashboards have been implemented into an organization, it is critical to govern their use to ensure the effectiveness and safety of the IT investment. The IT governance function is responsible for the control and direction of IT-related initiatives within an organization. Therefore, the implementation of AI-powered dashboards in an organization requires its IT governance function to thoroughly consider the relatively new concept of AI governance. The governance of AI is an essential part of IT governance as it aims to mitigate crucial AI-related risks influencing information security, data privacy, data accuracy, and transparency. Due to the complex and unpredictable nature of AI, as well as the recent emergence of AI governance as a crucial area of research, the scientific literature does not currently include a distinguished and widely recognized framework that addresses the governance of AI. The findings of this study indicate that the use of AI technologies can be governed through a comprehensive IT governance framework that has been adjusted into the context of AI governance. Scientific literature recognizes COBIT 2019 as an effective IT governance framework that has the potential to fit the purpose of AI governance to a certain extent through adjustments. Furthermore, the integration of multiple AI governance frameworks was identified as a competent solution to support the AI governance efforts of an organization. Although current scientific literature does not recognize a distinguished and comprehensive AI governance framework, research proposing comprehensive AI governance frameworks does exist. For instance, “The Hourglass Model of Organizational AI Governance” by Mäntymäki et al. (2022) could provide a competent and comprehensive solution regarding the governance of AI in organizational contexts.

Based on the findings derived from the literature review, this study proposes the appointment of an employee or a group of employees that is responsible for the governance of AI technologies within the IT governance function of an organization. In addition to the control and direction of AI technologies, the responsibilities of this role/function should include continuous maintenance of governance structures and

policies based on the persistent observation of technological developments in AI and scientific developments regarding AI governance. Enterprises possessing an IT governance function with a high maturity level are more likely to be capable of adjusting their existing governance structures and policies into the context of AI governance. On the contrary, enterprises with limited IT governance capabilities and low maturity levels, are more likely to govern AI successfully through the adoption of an integrated AI governance framework that utilizes a combination of individual frameworks.

6.2 Contribution

As AI-powered dashboards have not yet been widely implemented into organizational environments, the scientific literature does not include specific research regarding their adoption and governance. In case the deployment of AI-powered dashboards in organizational environments grows expectedly, the findings of this paper provide organizations with a theoretical foundation for their adoption and governance.

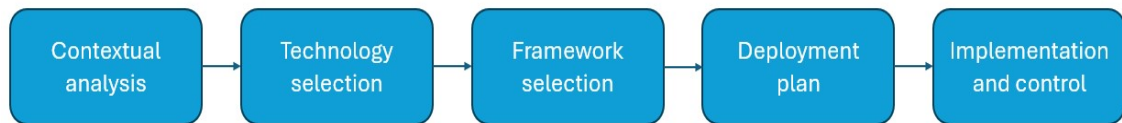


Figure 9. Adoption framework for AI-powered dashboards.

To illustrate the findings derived from the literature review on DDDM, AI, and IT governance, this thesis proposes two distinct theoretical frameworks addressing the adoption and governance of AI-powered dashboards. Figure 9 illustrates a theoretical process designed to support the adoption of AI-powered dashboards by dividing the process into five phases. Contextual analysis in phase 1 refers to extensive research on the internal and external environments of an organization. This includes the examination of technological needs, IT infrastructure, and technical capabilities of the workforce among other factors. Phase 2 includes the selection of a technology solution that fits the organizational context based on research in phase 1. Subsequently, phase 3 addresses the selection of an adoption framework that aligns with the organizational context and selected technology solution. Phase 4 includes the construction of a deployment plan based on the adoption framework selected in phase 3. The final phase addresses the actual

implementation of AI-powered dashboards which includes monitoring and controlling the process to prevent risks such as organizational resistance to change and neglect of the implemented BI tool.

Figure 10 demonstrates a theoretical process with four phases to support the governance of AI-powered dashboards in an organizational environment. Phase 1 examines the current IT governance function and identifies required changes to enable the governance of AI. Phase 2 includes the integration of AI governance into the IT governance function either through adjustments to the current IT governance framework or the implementation of an integrated framework utilizing multiple AI governance frameworks. Phase 3 addresses the creation of structures and policies that enable the governance of AI technologies based on the method selected in phase 2. The final phase addresses the continuous monitoring and evaluation of AI governance which prevents structures and policies from becoming obsolete due to frequent technological developments influencing the field of AI.

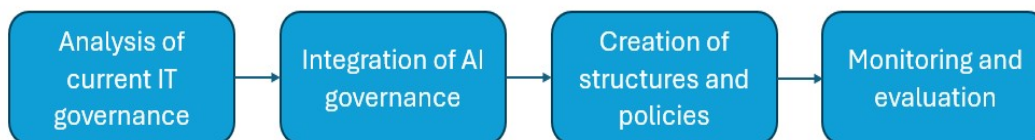


Figure 10. Governance framework for AI-powered dashboards.

6.3 Limitations and future research

Due to time constraints, the findings introduced in this study are entirely based on a literature review addressing AI-powered dashboards through the concepts of DDDM, AI, and IT governance. As a result, the contribution of this thesis is limited by its purely theoretical nature. As research on AI-powered dashboards is still in its preliminary stages, scientific literature addressing the concept is currently limited which additionally influences the content of this thesis. Furthermore, continuous technological developments occurring in the field of AI could impact the accuracy of the presented findings in the future. The influence of these limitations should be carefully considered regarding the potential utilization of findings and frameworks proposed in this thesis.

The contribution of this thesis could be complemented through empirical research on the implementation of proposed theoretical frameworks. Qualitative methods regarding

research on the proposed frameworks could include interviews and surveys addressing the adoption of AI-powered dashboards from the perspective of professionals leading the technology adoption and IT governance efforts of their organizations. Once scientific literature on AI-powered dashboards and AI governance has become more extensive, research on the adoption and governance of AI-powered dashboards is likely to introduce new insights that could complement the findings presented in this study. Additionally, a prominent direction for future research could address the use of AI-powered dashboards in more detail once the technology has been widely deployed into organizational environments. Research on the use of AI-powered dashboards could include studies on their functionality and personalization as well as comparative examinations between traditional dashboards and AI-powered dashboards.

7 Summary and conclusion

Three research questions addressing the current state of best practice dashboards as well as the adoption and governance of AI-powered dashboards are examined in this study through a literature review on dashboards and influential concepts closely related to the technology. The literature review identifies DDDM, AI, and IT governance as integral elements influencing the adoption and governance of AI-powered dashboards. Multiple more specific research areas within these concepts were additionally examined to provide a comprehensive understanding of factors influencing dashboard technology. Significant concepts examined within DDDM include dashboards in general, BI, DSS, EIS, and big data. Integral factors related to AI on the other hand include the general use of AI in DDDM, specific AI technologies utilized in dashboard development, and a practical method provided by SAP that currently enables the development of AI-powered dashboards in an organizational environment. The last segment of the literature review addressing IT governance examines BI governance, AI governance, and technology adoption as well as frameworks developed to support organizations in their efforts regarding these concepts.

Findings derived from the literature review conclude that AI technologies are utilized in dashboards to a certain extent. However, the technology has not been widely deployed in organizational environments. Additionally, the findings emphasize the importance of studying organizational contexts and utilizing a suitable theoretical framework to support the adoption and governance of AI-powered dashboards. These discoveries provide a basis for two theoretical frameworks proposed in this study. The first framework illustrates a five-phased process that can be utilized to support the adoption of AI-powered dashboards. Alternatively, the second framework addresses the governance of AI-powered dashboards by demonstrating a theoretical process consisting of four individual phases.

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Appendices

Appendix 1 COBIT Core Model (ISACA, 2018)



Appendix 2 Operational AI governance components, tasks, and literature streams (Mäntymäki et al., 2022)

Governance components and tasks	Description	Literature streams
A. AI system T1. AI system repository and AI ID T2. AI system pre-design T3. AI system use case T4. AI system user T5. AI system operating environment T6. AI system architecture T7. AI system deployment metrics T8. AI system operational metrics T9. AI system version control design T10. AI system performance monitoring design T11. AI system health check design T12. AI system verification and validation T13. AI system approval T14. AI system version control T15. AI system performance monitoring T16. AI system health checks	<p>Ensuring that the AI system is developed, operated, and monitored in alignment with the organization's strategic goals and values.</p>	<p>Software development and project management (Dennehy & Conboy, 2018)</p>
B. Algorithms T17. Algorithm ID T18. Algorithm pre-design T19. Algorithm use case design T20. Algorithm technical environment design T21. Algorithm deployment metrics design T22. Algorithm operational metrics design T23. Algorithm version control design T24. Algorithm performance monitoring design T25. Algorithm health check design T26. Algorithm verification and validation T27. Algorithm approval T28. Algorithm version control T29. Algorithm performance monitoring T30. Algorithm health checks	<p>Ensuring that the algorithms used by an AI system are developed, operated, and monitored in alignment with the organization's strategic goals and values.</p>	<p>Software development and project management (Dennehy & Conboy, 2018) Critical algorithm studies (Kitchin, 2017; Ziewitz, 2016)</p>
C. Data operations T31. Data sourcing T32. Data ontologies, inferences, and proxies T33. Data pre-processing T34. Data quality assurance T35. Data quality metrics T36. Data quality monitoring design T37. Data health check design T38. Data quality monitoring T39. Data health checks	<p>Ensuring that data are sourced, used, and monitored in alignment with the organization's strategic goals and values.</p>	<p>Data governance and data management (Abraham et al., 2019; Brous et al., 2016; Janssen et al., 2020) Critical data studies (Iliadis & Russo, 2016)</p>

<p>D. Risk and impacts</p> <p>T40. AI system harms and impacts pre-assessment</p> <p>T41. Algorithm risk assessment</p> <p>T42. AI system health, safety, and fundamental rights impact assessment</p> <p>T43. AI system non-discrimination assurance</p> <p>T44. AI system impact minimization</p> <p>T45. AI system impact metrics design</p> <p>T46. AI system impact monitoring design</p> <p>T47. AI system impact monitoring</p> <p>T48. AI system impact health check</p>	<p>Identifying, managing, and monitoring potential risks and impacts caused by the AI system to align the system with the organization's strategic goals and values.</p>	<p>Algorithmic impact assessment (Kaminski & Malgieri, 2020; Metcalf et al., 2021)</p>
<p>E. Transparency, explainability, and contestability (TEC)</p> <p>T49. TEC pre-design</p> <p>T50. TEC design</p> <p>T51. TEC monitoring design</p> <p>T52. TEC monitoring</p> <p>T53. TEC health checks</p>	<p>Ensuring that the AI system transparency, explainability, and contestability is aligned with the organization's strategic goals and values.</p>	<p>Explainable AI (Barredo Arrieta et al., 2020; Laato, Tiainen, et al., 2022; Meske et al., 2022)</p> <p>Algorithmic transparency (Ananny & Crawford, 2018; Wachter et al., 2017)</p> <p>Contestability (Almada, 2019; Floridi, 2018)</p>
<p>F. Accountability and ownership</p> <p>T54. Head of AI</p> <p>T55. AI system owner</p> <p>T56. Algorithm owner</p>	<p>Ensuring necessary decision rights and responsibilities to govern the AI system and its algorithmic components to align the system with the organization's strategic goals and values.</p>	<p>Algorithmic accountability (Martin, 2019; Shah, 2018; Wieringa, 2020)</p> <p>IT governance (Brown & Grant, 2005; Gregory et al., 2018; Tiwana & Kim, 2015; Weill, 2008)</p>
<p>G. Development and operations</p> <p>T57. AI development</p> <p>T58. AI operations</p> <p>T59. AI governance integration</p>	<p>Designing and implementing appropriate workflows and organizational structures for developing AI systems</p>	<p>Software development and project management (Dennehy & Conboy, 2018)</p> <p>DevOps (Gall & Pigni, 2021)</p> <p>MLOps (Mäkinen et al., 2021)</p>
<p>H. Compliance</p> <p>T60. Regulatory canvassing</p> <p>T61. Regulatory risks, constraints, and design parameter analysis</p> <p>T62. Regulatory design review</p> <p>T63. Compliance monitoring design</p> <p>T64. Compliance health check design</p> <p>T65. Compliance assessment</p> <p>T66. Compliance monitoring</p> <p>T67. Compliance health checks</p>	<p>Understanding the regulatory environment of an AI system and ensuring its compliance with the relevant regulations</p>	<p>Regulatory and legal studies (Kaminski & Malgieri, 2020; Viljanen & Parviainen, 2022)</p>

**Appendix 3 COBIT 2019 tailored to AI systems from the board perspective
(Reis et al., 2024)**

COBIT 2019 Governance and Management Objectives	Board of Directors Roles	Expected Benefits (Outcomes)
EDM01 - Ensured Governance Framework Setting and Maintenance	Set and maintain a governance framework that includes AI ethics, compliance, and strategic objectives.	Establishes a clear governance structure for AI, ensuring ethical use, compliance, and alignment with strategic goals.
EDM03 - Ensured Risk Optimization	Guide the balance between AI innovation and risk, ensuring risk optimization across AI initiatives.	Optimizes risk-taking, encouraging innovation while ensuring risks are managed effectively.
EDM05 - Ensured Stakeholder Transparency	Promote transparency in AI decisions, processes, and outcomes to build trust among stakeholders.	Enhances accountability and trust in AI practices, leading to better stakeholder engagement and support.
APO01 - Managed IT Management Framework	Oversee the establishment of a framework for AI governance that aligns with overall IT governance.	Ensures AI governance is integrated within the overall IT governance framework, leading to strategic alignment and responsible AI use.
APO02 - Managed Strategy	Ensure AI initiatives are in line with the organizational strategy and stakeholder needs.	Aligns AI initiatives with organizational goals and stakeholder expectations, driving strategic value.
APO03 - Managed Enterprise Architecture	Ensure AI is integrated within the enterprise architecture to support business outcomes.	Facilitates seamless integration of AI, ensuring it supports and enhances business processes and outcomes.
APO07 - Managed Human Resources	Oversee the development of skills and competencies needed for AI implementation and management.	Ensures the organization has the necessary talent and skills for AI, fostering innovation and operational excellence.
APO11 - Managed Quality	Ensure quality standards are applied to AI projects to meet business requirements and expectations.	Enhances the reliability and effectiveness of AI solutions, meeting or exceeding business and stakeholder expectations.
APO12 - Managed Risk	Ensure comprehensive AI risk management practices are in place, addressing ethical, privacy, security, and operational risks.	Enhanced risk management capabilities specific to AI, reducing negative impacts on reputation and operations.
APO13 - Managed Security	Guide the development and implementation of comprehensive security policies and practices for AI.	Strengthens the protection of AI systems and data, reducing vulnerabilities and enhancing trust.
BAI01 - Managed Programs and Projects	Sponsor and prioritized AI programs and projects based on strategic alignment and risk assessment.	Ensures AI projects deliver value, strategically aligned, and properly manage risks.

BAI05 - Managed Organizational Change	Oversee change management processes that facilitate the integration of AI into business processes.	Ensures smooth adoption of AI technologies, minimizing resistance and enhancing operational efficiency.
BAI09 - Managed Assets	Ensure proper management of AI-related assets, including data, algorithms, and intellectual property.	Protects valuable AI assets, ensuring their effective use and compliance with legal and ethical standards.
DSS01 - Managed Operations	Guide the operational management of AI systems to ensure efficiency and effectiveness.	Ensures AI systems operate efficiently and effectively, providing consistent value to business operations.
DSS04 - Managed Continuity	Oversee the development of AI systems with robust continuity plans, addressing potential AI-specific disruptions.	Ensures AI systems are resilient, minimizing downtime and maintaining business continuity in adverse situations.
DSS05 - Managed Security Services	Advocate for implementing advanced security measures for AI systems and data protection.	Enhances security posture, protecting AI systems and data against cyber threats and ensuring privacy compliance.
MEA01 - Managed Performance and Conformance Monitoring	Implement monitoring and reporting on AI performance and conformance to policies and regulations.	Provides oversight and insight into AI performance and regulatory compliance, ensuring continuous improvement.
MEA03 - Managed Performance and Conformance Monitoring	Ensure continuous monitoring of AI performance against governance objectives and regulatory compliance.	Enables ongoing oversight of AI initiatives, ensuring they meet performance objectives and comply with regulations.