THESIS / THÈSE

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A Methodological Framework Proposition to Integrate Hard Data and Experts' Knowledge

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"Nothing in life is to be feared, it is only to be understood. Now is the time to understand more, so that we may fear less."
Marie Skłodowska Curie

Abstract

A Strategy Map, an essential tool in the domain of strategic management, serves as a visual representation of the intricate network of interrelationships between a company's key performance indicators. This graphical framework empowers decision-makers by offering a comprehensive perspective on how a particular choice or action can ripple across all areas of an organization, yielding either positive or negative consequences. To this date, the large majority of practical development concerning Strategy Maps continues to rely heavily on the knowledge and intuition of experts within the organization. While these "*soft data*" have undoubtedly played a vital role in shaping effective strategies, they come with inherent limitations when it comes to the implementation of Strategy Maps. The limitations of soft data manifest in several ways. First, they can be marked by inaccuracies stemming from the subjectivity inherent in qualitative assessments. Second, these soft data can often result in gaps in completeness, potentially leading to an incomplete representation of the organization's complexities. Furthermore, a notable drawback is the lack of a longitudinal perspective, as these insights might not adequately capture historical trends or anticipate future changes in the business landscape. However, the contemporary technological context offers a transformative opportunity. Innovative tools for data collection, storage, and analysis have introduce an era of "*hard data*" — structured, quantitative information derived from various sources such as financial metrics, market trends, customer feedback, and operational statistics. These hard data have proven to be powerful assets, particularly as a foundation for enhancing strategic decision-making. In response to this paradigm shift, a compelling proposition arises: the integration of hard data into the development process of Strategy Maps to enhance their reliability, accuracy, and completeness. This transition holds the promise of advancing the field of strategic management, aligning it more closely with data-driven decision-making paradigms, and bridging the gap between traditional intuition-based strategies and the emerging data-driven approaches. This thesis dissertation embarks on the path of using hard data to refine Strategy Maps. Comprising four distinct studies, this

research project is dedicated to advancing the current body of literature in the field of strategic management. These studies encompass theoretical insights, innovative methodological propositions, and empirical demonstrations, all aimed at shedding light on the viability, challenges, and potential benefits of incorporating hard data into the creation and utilization of Strategy Maps.

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To my family: Maman, Papa, Marjorie, Mathilde, Chloé and my sweet goddaughter Romane, I'm forever grateful for your unconditional love and support although my work remained quite vague for you during these years.

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Contents

List of Figures

List of Tables

Acronyms

BSC ***Balanced Scorecard***, a strategic management framework that helps organizations to measure and monitor their performance across multiple perspectives, including financial, customer, internal processes, and learning and growth.
See also SBSC hereafter.

DM ***Decision-Making***, the cognitive process of selecting a course of action, choice, or judgment among various available alternatives. It involves assessing and evaluating the potential outcomes, risks, benefits, and consequences of different options before arriving at a conclusion or making a final choice.

KPI ***Key Performance Indicator***, a measurable value that demonstrates how effectively an organization is achieving its key business objectives. They are typically chosen based on a company's strategic goals and can be used to track progress over time, identify areas that need improvement, and make informed decisions to optimize performance.

SM ***Strategy Map***, a visual tool used to communicate an organization's strategy in a clear and concise manner. It is typically a one-page document that displays the cause-and-effect relationships between the KPIs of a company. The strategy map is often used in conjunction with the balanced scorecard, a performance management tool that helps organizations track progress toward strategic objectives.

SBSC ***Sustainable Balanced Scorecard***, a strategic management tool that extends the principles of the traditional balanced scorecard to incorporate sustainable practices and long-term environmental, social, and economic considerations. It aligns business strategies with sustainability objectives, allowing organizations to evaluate and track their performance in achieving sustainability goals.

Part I – Introduction

General introduction

Research context

Organizations are facing a world known as "VUCA" for Volatile, Uncertain, Complex, and Ambiguous (Sinha & Sinha, 2020), and what was true yesterday no longer holds. The traditional strategic objective of "financial results" no longer applies, and modern organizations are expected to excel simultaneously in a variety of areas, including financial, but also human resources, sustainability, marketing, and operations, among others. The problem that most organizations encounter when attempting to do this is that decisions made to improve performance in one area can positively or negatively affect other areas, leading to a highly complex decision framework. For example, a choice made to enhance sustainability may have a negative impact on operations, a positive impact on the social dimension, and be neutral for the financial dimension. As a manager, not having a clear understanding of the interaction between the different strategic areas of the organization is akin to navigating blindly. The risks of getting lost or making a wrong decision become significant and unacceptable. To mitigate these risks, organization leaders need a clear and comprehensive view of the various strategic domains they must manage and how these domains are interconnected. Given the importance of the decisions to be made, this vision must be *accurate*, *valid*, *robust*, and *adaptable* to changes in the world.

Corporate strategy is complex and typically determined by internal experts (board of directors, C-suite) or external consultants. Managers often find themselves at a crossroad when it comes to making crucial decisions for their organizations. They can either base their choices on their wealth of expertise, intuition, experience, and judgment or opt for a more factual and data-driven approach. When relying on their personal know-how and instincts, decision-makers may analyze and formalize their strategies with a certain level of subjectivity. In such instances, available data serves as a means to validate their ideas rather than guiding the DM process. This approach carries an inherent risk, as it can lead to a limited and potentially biased perspective of the organizational reality, leaving room for potential oversights and missed opportunities. Literature regularly discusses the inclusion and use of Artificial Intelligence and Data Analysis in strategic DM (Trunk et al., 2020). In the field of scientific research, the conventional approach often involves incorporating human involvement in DM, *after* the completion of data analysis or tool construction. However, our pioneering approach takes a distinct path by placing human expertise and data at the very core of the tool's *design*, setting the stage for enhanced usability and effectiveness in DM applications. In addition, only a handful of works focus on researching causal relationships in strategic tools, and even fewer tackle the concept of hybridity. In this thesis, we challenge this approach by systematically juxtaposing the experience of decision-makers with the reality of data. We test numerous combinations of possible indicators, seek causality relationships between them, and present these findings to decision-makers for effective synergy. We focus on detecting and validating underlying causal links between the KPIs of organizations. Our work offers a primary advantage over existing approaches through *hybridization* of data sources. Hybridization refers to the combination of domain expertise and the power of quantitative data analysis to provide reliable strategic tools. These two approaches, often seen as opposing, are in reality complementary, as the disadvantages of one can be mitigated by the advantages of the other.

When developing a strategy, a multitude of powerful tools are available to guide and inform the process (Lynch, 2006). These tools provide organizations with valuable frameworks and insights to ensure that their strategies align with their goals and the ever-evolving business landscape. Among traditional tools, we encounter the *SWOT* analysis which helps in identifying internal strengths and weaknesses, along with external opportunities and threats. Porter's *value chain* and *Five Forces* models help analyze competitive advantages and market dynamics. The *PESTEL* analysis delves into macro-environmental factors, and the *VRIO* framework evaluates internal resources and capabilities. More recently, new tools and framework have appeared such as the *Hoshin Kanri* matrix which facilitates the cascading of objectives and promotes cross-functional collaboration. *Objectives Key Results* helps in setting and tracking goals with measurable outcomes. The *Business Model Canvas* and *Lean Canvas* are templates used for developing new business models. These tools, each with their own specificities, collectively empower decision-makers to make informed and well-structured strategic choices. Throughout the entire thesis, the *Strategy Map* will serve as the primary illustration of strategic DM tools. A SM is a visual tool used in strategic management to illustrate the key strategic objectives of an organization and the cause-and-effect relationships between them (Kaplan & Norton, 2000). It was developed in 2000 by two American authors, Robert Kaplan and David Norton, as an extension of their other, well-known concept: the BSC (Kaplan & Norton, 1992). The SM provides a clear and structured view of how various strategic goals and initiatives are interconnected and contribute to the achievement of an organization's overall mission and long-term vision. By using a SM, organizations can effectively communicate their strategic vision, align their teams, and ensure that everyone understands how their efforts and decisions impact the attainment of strategic goals.

Our choice to explore the SM stems from several compelling reasons. First and foremost, SMs enable a holistic approach to strategic management which considers financial, customer, internal processes, and learning and growth perspectives. As a result, the SM provides a comprehensive view of strategy execution, making it a critical element in contemporary strategic management. Second, the SM has the advantage to be at the crossroad of the fields of "strategy" and "decision-making". These two fields are distinct yet inherently interconnected for organizational management. Strategy is the formulation of long-term objectives, the direction an organization seeks to take, and the competitive advantage it aims to establish. DM, on the other hand, encompasses the process of selecting from various available options to achieve specific goals, often involving complex choices influenced by internal (including strategy) and external factors. SMs emerge as a remarkable juncture, bridging the gap by offering a visual representation of an organization's strategic objectives and the cause-and-effect relationships between these objectives. In doing so, SMs facilitate not only the communication of the strategic vision but also help decision-makers in understanding how specific actions and initiatives can contribute to the realization of strategic goals.

In the same way as defining a company's strategy, the construction of the SM is primarily based on the expertise of an organization's managers. Thus, SMs also suffer from the same potential biases, shortcomings, or inaccuracies. This thesis investigates and suggests a novel approach to design the SM tool by incorporating empirical data into the process.

Research objectives and assumptions

This thesis' research objective is to provide theoretical insights, methodological recommendations, and empirical evidence to advance the existing literature in the field of strategic and performance management by introducing an innovative approach that integrates empirical data and human expertise. In pursuit of this objective, this dissertation will present four studies and address the research questions presented in Table 2.

Chapters	**Research question(s)**
Chapter 1	**RQ1.** "How did the literature about Strategy Maps design evolve over the past two decades?" **RQ2.** "What are the trends in terms of methods and methodology types for Strategy Maps design?" **RQ3.** "What are the trends in terms of data sources for Strategy Maps design?"
Chapter 2	**RQ.** "How to integrate factual data in the design of Strategy Maps?"
Chapter 3	**RQ1.** "What are the comparative strengths and challenges associated with the different architectures in the construction of a SBSC?" **RQ2.** "What are the comparative strengths and challenges associated with the different architectures in the use of a SBSC for decision-making purposes?" **RQ3.** "What are the most recommended and discouraged application cases for each type of SBSC architecture?"
Chapter 4	**RQ.** "How can an organization integrate its human expertise and factual data to build more valid and robust SMs?"

Table 2: Summary of research questions of this dissertation

In the investigation of our research questions, it is imperative to understand the different keywords that will be used throughout the Chapters of this thesis, more specifically the difference between *hard* and *soft* data. Both hard and soft data can be either qualitative (categories, qualities, characteristics,...) or quantitative (numerical), what distinguishes the two is the provenance of the information. Soft data, also written as (experts) *knowledge* or (experts) *intuition* in the following Chapters, is information provided by humans. This type of data is more intangible, hard to measure, and can differ from one (group of) person to another. On the contrary, hard data, or sometimes simply called *data* in this thesis, is factual, objective, and quantifiable information that is typically expressed in numerical or statistical form, making it measurable and easily analyzable. Hard data can be qualitative when the measure is transformed into a categorical scale (see example below). Considering these definitions:

- *The average score of employee satisfaction* will be considered in this thesis as soft (provided by humans) and quantitative (numerical) data;
- *The classification of a situation to be risky/not risky by the employees* is considered as a soft (provided by humans) and qualitative (categorical) data;
- *The yearly sales of an organization* is considered as hard (measured) and quantitative (numerical) data; and
- *The classification of the outside temperature as high/medium/low* is considered as hard (measured) and qualitative (categorical) data.

Based on the above definitions, the underlying assumptions which guided our research approach and shaped our perspectives in this thesis are:

1. *Hard data and subsequent data analyses is one relevant way to access the truth:* This assumption posits that data-driven insights are accurate and reliable in decision-making. As an example, hard data used in crime statistics in a specific region is a relevant means to access the truth. By analyzing concrete numbers of reported incidents, law enforcement and policymakers can objectively identify patterns, allocate resources effectively, and formulate evidence-based strategies.

2. *Hard data can allow fast decision-making, thanks to automation:* This assumption highlights the efficiency gained through automating processes with hard data. For instance, an e-commerce platform employing automated algorithms can rapidly adjust the pricing based on sales (hard) data, optimizing revenue.

3. *Integrating data and intuition could bring another level of certainty and robustness:* This assumption suggests that combining data-driven analysis with human intuition can lead to more robust and certain DM. This assumption holds especially when the information needed to make decisions in an organization has to take into account both intangible, experience of managers and tangible, hard data inputs.

4. *Integrating data and intuition is challenging:* This assumption recognizes the challenges and complexities in effectively blending data and human judgment. This is particularly evident in fields like artificial intelligence, where building algorithms that can understand human context and nuances remains a significant challenge.

5. *A robust DM support tool is handy for organizations in this complex world:* This assumption underscores the value of decision support tools, such as SMs, which provide organizations with insights to navigate today's uncertain and dynamic business environment.

Research methodology

To address our research objective, we carry out a Design Science Research (DSR) methodology throughout the entire thesis. DSR methodology centers around building and evaluating new or improved IT artifacts designed to enhance the capabilities of individuals and organizations (Hevner et al., 2004). DSR is a research paradigm that is particularly well-suited for investigating and solving complex problems in various domains but particularly in information systems and information technologies, by providing a systematic and iterative framework for designing and evaluating innovative artifacts. Through the systematic application of

DSR, we aim to not only gain insights into the identified challenges within strategic decision-making presented in the research context but also to contribute with a practical solution which can positively impact the field.

The adoption of the DSR methodology for reaching our research objective is justified by its problem-solving, double (theory and practice) approach, and iterative characteristics. Indeed, DSR follows a problem-solving approach, emphasizing the creation of practical solutions to real-world problems (Hevner, 2007). This characteristic of the DSR methodology makes it relevant for this thesis objective: to help organizational decision-making problems by introducing an innovative approach that integrates empirical data and human expertise. Moreover, DSR is a methodology to design an artifact both *from* and *for* theory and practice, iteratively. It begins by grounding the artifact construction in business needs and existing knowledge. The resultant artifact is then implemented in its relevant environment, contributing to the knowledge base and establishing new theoretical and practical foundations for new iterative artifact constructions. This process is depicted through two cycles: the relevance cycle for practice and the rigor cycle for theory. Lastly, in our research, where the goal is to design an effective solution, the iterative nature allows for continuous refinement and improvement of the proposed solution in the environment and literature.

Figure 1 represents the three cycles applied to this dissertation. The *environment* related to the application of our DSR methodology considers three key elements: People, Organizations, and Technology. People include decision-makers at the top (C-suite) which will make use of the new artifact, business experts which takes place in the design of the artifact, and external stakeholders. Organizations involve those with advanced data practices and strategic maturity, evolving in a complex and unpredictable environment (VUCA). Technology in this environment encompasses information systems, data storage and security, and key performance indicators of the organizations.

The *relevance cycle* is achieved through constant collaboration between theoretical design and real-world application. By employing a genuine case study and seeking validation from business experts, we

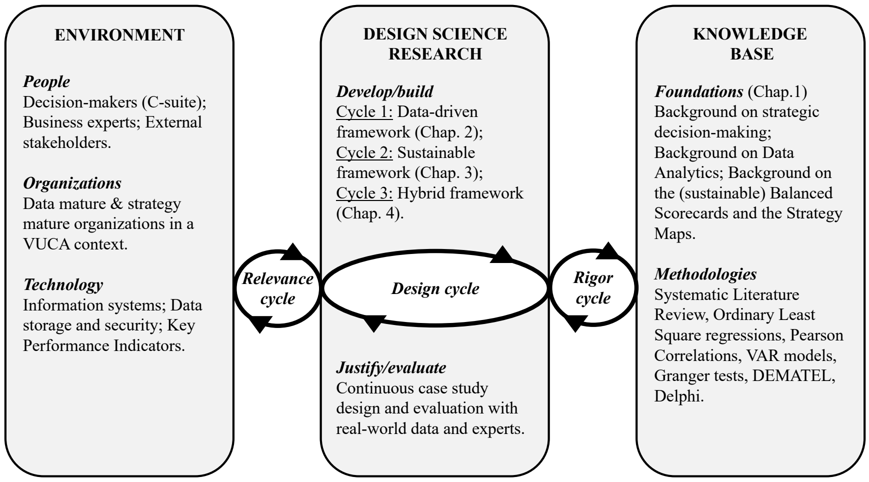

Figure 1: Application of the three cycles to this dissertation

ensure that our research is closely aligned with practical contexts. This iterative process, marked by a dynamic exchange, enhances the applicability and effectiveness of our design. The involvement of business experts provides valuable insights which helped improving our artifact in each design cycle. In each cycle, we contribute to the environment by introducing updated, improved framework processes.

The *knowledge base* establishes a strong foundation in Chapter 1, delving into crucial aspects like strategic decision-making, data analytics, and the sustainable Balanced Scorecards and Strategy Maps. This foundational Chapter ensures a comprehensive understanding of the key elements that shape our research. Second, methodologies carried out during the different iterations are strongly grounded in the literature as well. The systematic literature review methodology helps us build on existing knowledge, while statistical methods like Ordinary Least Square regressions, Pearson Correlations, VAR models, Granger tests, or qualitative methods such as DEMATEL and Delphi provide robustness of our designed artifact.

The *rigor cycle* is made possible by starting with what already exist in the literature and as methodologies. As we move through each design cycle, we explore new methods from the knowledge base. This back-and-forth process ensures that our research stays relevant, incorporating the latest insights from the field literature. We provide advances back to the knowledge base through the exploration and application of our DSR.

The *artifact* we aim to develop is an innovative approach to guide strategic decisions in organizations. The following dissertation presents three *design cycles* which are building upon each other. The starting artifact is the SM. In *design cycle 1*, after noticing a lack of hard-data quantitative models to build SM, we created and tested a new data-driven framework to fill this gap. This cycle sets the foundation for our research, providing a starting point for further improvements and developments in our artifact. In *design cycle 2*, we verify whether our newly data-driven framework stays consistent in different situations. We here test it with a modified SM focused on sustainability. This helps us see if our approach is flexible and can be useful for other changes, like IT, digital transformation, human resources,... The feedback from the two first cycles is that data is in fact helpful and can be used but don't hold all information and are not always reliable. The recommendations from the environment is to integrate back the human in the process and create a hybrid artifact. In *design cycle 3*, we modify our data-driven artifact to design a hybrid artifact of both human insights and data. This change ensures that we give equal importance to both people and information and that adoption of the strategic tool is higher. The knowledge base foundation and the three design cycles correspond to the four Chapter of the present manuscript.

Outline of the thesis

This thesis explores the evolution of SMs in the light of information management, advancing from intuition-based designs to data-driven and hybrid methodologies. It proposes hybrid frameworks, combining organizational data and expert knowledge and intuition, to enhance strategic DM and also investigate the integration of sustainability into the strategic tool. The thesis manuscript is composed of three parts described below.

Part I of this manuscript is composed of a general introduction to the thesis, and the state of the art in the strategic and performance management field, more specifically on SMs and the BSC.

Part II is the central piece of this dissertation, composed of four Chapters as describe in Figure 2.

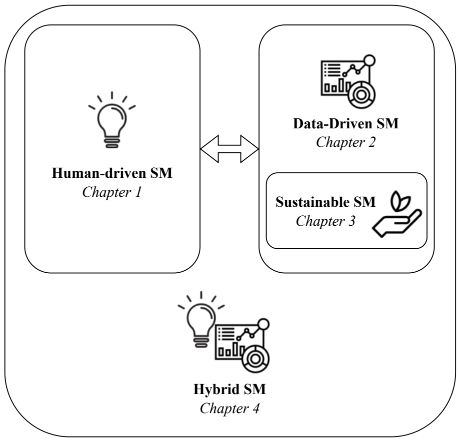

Figure 2: Summary of the four Chapters of this thesis

Chapter 1: Unveiling the Landscape of Strategy Maps. The first Chapter takes a deep dive into the world of SMs by reviewing existing literature. This review sheds light on the prevalent use of SMs as tools for strategic DM. It demonstrates that these tools are often shaped by intuitive insights (which we call "soft data") derived from managers' experiences and qualitative methodologies. By synthesizing these findings, we lay the foundation for the subsequent Chapters, setting the context for a practical and actionable approach.

Chapter 2: Navigating Data-Driven Horizons. Building on the insights from the literature review, the second Chapter addresses the challenges associated with relying solely on soft data for SM design. This Chapter proposes a straightforward methodological framework that advocates for the integration of tangible organizational data, referred to as "hard data". This pragmatic shift is intended to bring a higher level of objectivity and precision to the SM design process, thus making it more applicable in real-world DM scenarios. We demonstrate the feasibility and relevance of this methodology using data from skeyes, the Belgian air traffic control company.

Chapter 3: Connecting Strategy and Sustainability. This

Chapter expands the horizons of the strategic tool by integrating the concept of sustainability. Building upon the data-driven framework proposed in the previous Chapter, this Chapter conducts an empirical comparison of four sustainable architectures detailed in existing literature. Through this analysis, a comprehensive understanding of each architecture's advantages and limitations is gained, opening more discussion around this strategic tool.

Chapter 4: Finding Common Ground Through a Hybrid Approach. The final Chapter introduces an innovative hybrid framework to design SMs. This approach thoughtfully combines the strengths of both hard and soft data sources, recognizing their potential complementarity. By embracing this synergy, the proposed hybrid framework seeks to maximize the benefits of each data type while mitigating their respective limitations. This Chapter underscores the potential for enhanced strategic insights that arise from merging these seemingly distinct data sources.

Finally, **Part III** concludes the manuscript with a summary of the findings, the contributions of this thesis, challenges, limitations and further research directions as well as the scientific portfolio of the author.

Literature review

Management, strategic management and strategic decision-making

Management has a long history that can be traced back to ancient civilizations. Even in the earliest times, rudimentary forms of organization and coordination were evident in various activities. But is was the Industrial Revolution which brought a significant changes in organizational structures and led to new management practices. The establishment of large-scale factories and the increased complexity of industrial processes necessitated a more systematic approach to optimize productivity. In the late 19$^{\text{th}}$ century, Frederick Taylor, often referred to as the father of scientific management, introduced principles that focused on the scientific analysis of tasks, time and motion studies, and the standardization of work processes.

Management can be defined as the process of *planning*, *organizing*, *commanding*, *coordinating*, and *controlling* within an organization to achieve specific goals and objectives (Fayol, 1918). It involves coordinating the efforts of *people* to efficiently and effectively utilize available *resources* in order to accomplish the organization's mission and vision.

Nowadays, the branches of management include financial management, marketing management, sales management, human resource management, strategic management, production management, operations management, and general management, among others. This dissertation focuses on strategic management. Strategy is defined as the "*long-term direction of an organi[z]ation*" (Johnson et al., 2020, p.4). Strategic management is thus concerned with the formulation and implementation of strategies to achieve the long-term goals of the organization and improve firm performance.

Strategic management involves analyzing the internal and external environment, identifying strengths, weaknesses, opportunities, and threats, and developing plans and policies to achieve a competitive advantage. It is an ongoing process that requires continuous planning, monitoring, analysis, and assessment of all the factors necessary for an organization to meet its goals and objectives.

Managers in strategic management roles are often responsible for making high-stakes decisions that can have a significant impact on the organization. Strategic DM is a critical component of organizational management, as it involves making choices that have a long-term impact on the organization's overall direction and goals. Strategic DM can be understood as the process of focusing on the most important decisions that need to be made in order to achieve the organization's strategic goals. The strategic DM process can be broken down into seven steps summarized in Figure 3.

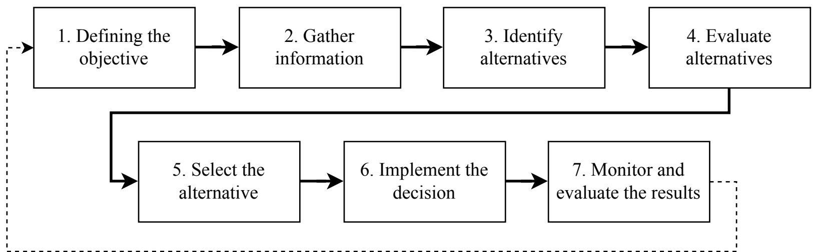

Figure 3: Steps of DM, adapted from Negulescu (2014, p.114)

The first step is to identify the problem or opportunity that needs to be addressed. This may involve conducting an external and internal analysis of the organization. Once it is clear about the decision that needs to be made, it is necessary to gather as much relevant information as possible. This may include conducting market research, analyzing financial data, or talking to stakeholders. Once the problem or opportunity has been identified, the next step is to generate a list of possible solutions. This can be done through brainstorming, research, and consultation with experts. With the list of alternatives, the next step is to evaluate each one in terms of its potential benefits, costs, risks, and feasibility. Then, the next step is to make a decision regarding the alternative to select. This may involve weighing the pros and cons of each alternative, making a subjective judgment, or using a DM tool such as a cost-benefit analysis. After, once a decision has been made, it needs to be implemented effectively. This may involve developing a plan, allocating resources, and communicating the decision to those affected by it. Finally, it is important to monitor the results and to make adjustments as needed. This will help to ensure that the decision is achieving its desired outcome. In this dissertation, we are concerned with steps 3, 4 and 5. Indeed, we are focusing our research studies on the way to build robust tools to help decision-makers to understand *what choices they have* and *what impact(s) their choice will have on the organization*.

Strategic DM is important for all organizations, regardless of size (Dean Jr & Sharfman, 1993), industry, or sector. However, it is especially important for organizations that operate in complex and dynamic environments. In these environments, managers need to be able to make quick and effective decisions in order to adapt to changes and stay ahead of the competition. We collaborate with the Belgian Air Traffic Control Company throughout 3 cases studies in this thesis. The aviation industry is certainly running activities in a complex and dynamic environment, which increases its need for a robust strategic DM tool. There are a number of different factors that managers need to consider when making strategic decisions. These factors include the organization's mission and vision, its internal capabilities, and the external environment (Rajagopalan et al., 1993).

The landscape of strategic DM has transformed significantly over the decades. Historically, decisions were often made based on intuition and experience, with a strong emphasis on decision-makers' profiles (Langley et al., 1995). However, as businesses encountered an increasingly global and competitive marketplace, they recognized the need for a more structured approach. This led to the development of formal strategic planning processes that relied on data, market analysis, and scenario planning. These early steps toward a more systematic approach laid the foundation for the sophisticated DM methodologies we employ today. The digital revolution has transitioned in a new era of strategic DM (Berntsson Svensson & Taghavianfar, 2020). Today, organizations harness the power of advanced analytics, big data, and artificial intelligence to inform their decisions (Elgendy & Elragal, 2016). These technologies enable them to not only collect and process vast amounts of data but also to extract valuable insights that were previously hidden. In this data-driven age, organizations can make decisions with a higher degree of accuracy and anticipate market trends with greater precision.

In the quest for better strategic DM, organizations have turned to a diverse array of performance measurement and DM tools. These tools serve as invaluable instruments for gathering, analyzing, and interpreting data, enabling organizations to make informed choices. The utilization of such tools has become a necessity, given the increasing complexity of modern business environments and the need to respond rapidly to changing circumstances. One of the most common and utilized tool is the BSC (Kaplan & Norton, 1992) and its SM (Kaplan & Norton, 2000), the latter is studied in this dissertation.

Balanced Scorecard and the Strategy Map

Definition and example

In 1992, the BSC marked a pivotal moment in the evolution of strategic DM. It recognized that traditional financial metrics alone were insufficient to gauge an organization's performance and alignment with its strategic goals. The BSC is a performance management framework that integrates financial and non-financial measures to assess organizational performance (Kaplan & Norton, 1992). It is based on the idea that organizations need to focus on four key perspectives:

- *Financial Perspective:* This perspective assesses the organization's financial performance and its ability to generate value for shareholders;
- *Customer Perspective:* The focus is on customer satisfaction, loyalty, and retention – key indicators of an organization's ability to meet customer needs;
- *Internal Business Processes Perspective:* This perspective evaluates the efficiency and effectiveness of an organization's internal processes, highlighting areas for improvement;

- *Learning & Growth Perspective:* The last perspective assesses an organization's capacity for innovation, development, and adaptability, which are critical for long-term success.

About a decade later, the two creators of the BSC have extended the concept and have developed the SM, a additional tool based on the BSC (Kaplan & Norton, 2000). The SM provides a visual representation of an organization's strategic objectives and the cause-and-effect relationships between them. The added value of SMs comes precisely from the presence of these cause-and-effect relationships between the indicators, it is the core element of the tool.

The most recent bibliometric analysis on BSC demonstrates the importance of SM in the BSC concept. That the keyword "*Strategy Map*" is the third most important keyword when looking for the keywords "*BSC*" and "*Performance Measurement/Performance Management*" (Suárez-Gargallo & Zaragoza-Sáez, 2023). Islam performed a literature review to deduce 14 design principles to guide practitioners to develop a customized SM (Islam, 2018) and presented the evolution of the SM of an organization over time and highlight a link between use and design/change of SM (Islam, 2019).

Figure 4 presents a simple and fictive illustration of a SM. With this simplified example, we see that capturing the causal relationships that occur between the key indicators of a company is very essential for two main reasons. First, it helps the decision-makers to confidently understand the impact of a decision on others indicators: if the *'Defective item rate'* increases, we instantly see that this will directly impact the *'Customer satisfaction level'* and the *'Gross margin'*. Second, the SM is also an opportunity to be able to influence intangible indicators such as the *'customer satisfaction level'* by playing on causing indicators such as the *'Production lead time'* or the *'Defective item rate'* which act as levers.

Many SM characteristics are shown in this simple example. According to the rule of the creators of the SM, the causal links can only happen within the same perspective or toward any upper perspective, which is represented here. In this thesis, we tried to stick to the strict definition of the SM by the two American authors and we do not analyze or showcase any downward causal links. We deviate slightly from the characteristics of the SM in this dissertation in two ways: as will be shown in Chapter 2, we allow some bi-directional relationships between KPIs. Indeed, it has been practically demonstrated that both KPIs where causally impacting the other. We did include both relationships in the SM as we believe this becomes relevant information for decision-makers. Secondly, again in Chapter 2, we have a disconnection between the bottom perspective and the three other perspectives. This was unintentional and the reasons we observe this disconnection might be due to the very small amount of (eight) KPIs used to demonstrate our artifact in this particular Chapter. Otherwise, the SM tool is designed to have all KPIs and all perspectives interconnected from the bottom up.

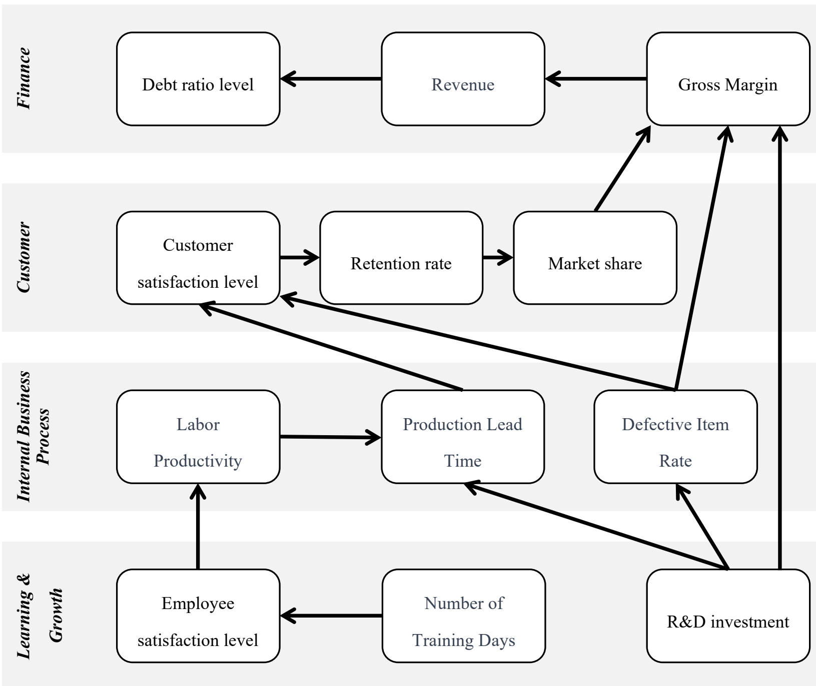

Figure 4: Simple example of a SM

The use of SM in organizations

Creating a SM has been recognized as essential for firms in the literature. Indeed, not linking indicators nor validating those links is the cause of failure of performance models such as the BSC and companies that successfully build their SMs experience higher returns on investments and in equity (Ittner & Larcker, 2003). In practice, SMs (and BSCs) are utilized by company for multiple reasons. First, SMs can help in strategic formulation (Kaplan & Norton, 2000) by providing a visual framework for evaluating potential initiatives and projects. When faced with strategic decisions, organizations can refer to their SM to assess alignment with their objectives. By offering a comprehensive view of the organization's strategy and objectives, SMs enable more informed and strategic DM. This can lead to improved overall performance and a better chance of achieving long-term success (Cheng & Humphreys, 2012; Wiersma, 2009). Second, SMs serve as effective communication tools (Kasperskaya & Tayles, 2013; Ritter, 2003), allowing leaders to convey the organization's strategy to employees, stakeholders, and investors in a straightforward and visually engaging manner. This clarity of communication ensures that everyone is on the same page regarding strategic direction. Finally, SMs are often used to control (Malina et al., 2007) the organization. By displaying the interconnections between objectives, departments, and initiatives, SMs ensure that all efforts are directed toward achieving the overarching strategy. This facilitates the measurement of progress and holds individuals and teams accountable for achieving specific goals.

SM design methodologies

There are numerous methodologies to construct a SM. For instance, Asgari and Darestani (2017) demonstrates that a large proportion of BSC development has been carried out through multi-criteria decision making methods such as AHP (Leung et al., 2006; Quezada & López-Ospina, 2014), ANP (Leung et al., 2006; Quezada et al., 2014), DEMATEL and TOPSIS. Moreover, adapted versions of the previously mentioned ones have been applied to counter the subjectivity part underlying these methodologies such as the fuzzy-DEMATEL (Jassbi et al., 2011), fuzzy cognitive maps (Chytas et al., 2008, 2011; Jassbi & Mohamadnejad, 2011; Mohamadnejad & Jassbi, 2012). Other, more peculiar, methods have been investigating such as the response surface methodology (Farokhi & Roghanian, 2018), scenario planning (Jafari et al., 2015). On a more quantitative side, Keshavarznia et al. (2020) use Granger causality test to design the SM and Thakkar et al. (2007) carry out an interpretive structural modeling methodology, among other examples.

Further investigations about the SMs design methodologies (methodology type and data source) are demonstrated in Chapter 1. While the methods for building strategic models have evolved over the past two decades, they still heavily depend on human inputs even when quantitative techniques are employed. On the other hand, the advent of digitalization has enabled companies to amass an unprecedented amount of data. To maintain their competitiveness, organizations harness this data to formulate strategies and inform DM. This thesis takes a fresh perspective on the strategic modeling tool, introducing data integration into the process. We will explore a hybrid approach to strategic models, either as a comparison to or a complement for the more conventional human-driven models.

Applications Fields

SMs and the BSC find extensive application across diverse fields and industries in the literature which demonstrates that this tool is designed to be valuable across diverse applications. The application fields of the SM is further developed in Chapter 1 but we present the most represented. The medical sector is a sector which have been investigated in the case of BSC and SM building. For example, Urrutia and Eriksen (2005) developed a BSC in the health-care management context and Leksono et al. (2019) built a BSC for sustainable healthcare supply chain. SMs for higher education has been studied multiple times. For instance, Papenhausen and Einstein (2006) created a BSC for a college of business, Umayal Karpagam and Suganthi (2012) develop a BSC in academic institution or Serdar Asan and Tanyaş (2007) constructed a BSC for higher education. The information technology field has examples of SM case study in the literature, Mair (2002) designed a SM for a small software group to link and align strategy with the operational tasks that employees perform and Papalexandris et al. (2004) developed a BSC for software firm. Huang et al. (2006) built a BSC for information security management. In manufacturing sector, Zhang and Huang (2012) designed a BSC in the Performance Management of Service-Oriented Manufacturing Enterprises. Nauhria et al. (2018) built a SM for a car manufacturing industry. Eftekhari and Torabi (2022) developed a SM for an iron and steel company. Regarding hotel and hospitality, Kala and Bagri (2016) created a SM for hotel industry. Doran et al. (2002) designed a BSC for the hospitality industry. Chen et al. (2011) used a combination of DEMATEL and ANP to produce a SM for Hot Spring Hotels. Finally, many other sectors have been investigated such as banking institutions (Wu, 2012), forensic accounting (C.-H. Yang & Lee, 2020), public utilities (Bianchi & Montemaggiore, 2008), construction company (Chan, 2009), or in supply chain management (Okongwu et al., 2015), among others.

A short note on sustainable SM

In recent years, the BSC and the SM have regained attention in the literature by incorporating a contemporary concept: *sustainability*. This illustrates a growing recognition of the crucial connection between corporate performance and global sustainability challenges, making the BSC and the SM valuable tools for organizations to track and manage their environmental and social impact. Gminder and Bieker (2002) and Dias-Sardinha et al. (2002) might be the first authors to do studies on what was then called 'sustainability-BSC', where an evolution of the traditional BSC took place. In 2013, Nikolaou and Tsalis (2013) proposes a SBSC framework. Then, Hansen and Schaltegger (2016) published a systematic review of architectures of the sustainability BSC. Sustainability in the BSC and the SM is further developed in Chapter 3 of this thesis.

Strong debates in the SM community

In the early 2000's, authors began to scrutinize the SM tool to highlight shortcomings. The subsequent years witnessed a back-and-forth in the literature with criticisms and defenses of the tool.

Hanne Nørreklit (2000) provided a critical analysis of two fundamental assumptions of the BSC: the causal relationships and the measurements. First, Nørreklit argues that some causalities assumed by Kaplan and Norton are not valid in real cases (Nørreklit, 2000). As a response, advocates of the BSC framework, Bukh and Malmi, stated that Kaplan and Norton's intention was not to create a generic model – which, if applicable to all companies as such, would lose its strategic benefit for competition – but wanted a model based on assumed relationships between a selection of indicators in a certain company at a certain point in time (Bukh & Malmi, 2005). None of the causalities are pre-established but rather assumed by the managers and revised if proved wrong later. The authors also admit that, ideally, the relationships should be validated with data if available. Nørreklit also question the relationships between the four perspectives stating that there exist interdependence instead of causality (Nørreklit, 2000). Once again, Bukh and Malmi replied that these relationships could be indeed interdependent in practice but that the backward link only reflects feasibility and should not be taken into account in the SM (Bukh & Malmi, 2005). The second assumption the Nørreklit challenges is that it is possible to measure and track all of the important aspects of organizational performance. However, the author argues that some intangible factors, such as employee motivation and organizational culture, are difficult to measure and quantify.

Eight years later, Norreklit et al. (2008) highlighted several pitfalls in using the BSC. The first pitfall is the oversimplification, as organizations are complex but the BSC is too simple, it does not fit all business circumstances. The second pitfall is the lack of inclusion of the assumptions underlying causal relationships. A third pitfall concerns the lack of time dimension in the BSC. Indeed, cause-and-effect relationships require a time lag between the cause and the effect. It is problematic that the time dimension is not an explicit part of the scorecard. Another pitfall is the managerial remoteness, as managing from the 'cockpit' and staying away from operational reality can be dangerous. The last pitfall is more general, it explains that poor measures leads to poor management (summarized by the famous saying: *garbage in, garbage out*).

Finally, Abernethy et al. (2003) highlighted difficulties in building performance measurement models such as the BSC because some causal relationships reside in tacit expert knowledge. The same year, Ittner and Larcker (2003) do not criticize the SM tool in itself but the bad application of it and more particularly, the lack of validation between the cause-and-effect which ultimately impact the organization's performance.

Active contributors of the field

In the literature on SMs, an exceptionally active research team has gained notable recognition for their extensive portfolio of publications, consistently investigating various aspects of the strategic tool, thereby enhancing its theoretical foundations and practical applications.

Researchers Louis E. Quezada, Héctor A. López-Ospina, Felipe Acuña-Carvajal and their colleagues began their research endeavor on SMs in 2007 by presenting a straightforward tool for developing SMs, by analyzing various companies' approaches and synthesizing a simplified method for defining strategic objectives and performance indicators, while also examining the types of indicators used by these organizations (Quezada et al., 2007). Two years later, they published a follow-up paper focused on the identification of strategic objectives in the SMs (Quezada et al., 2009).

From 2013 and on, they started to innovate on designing SM and proposed a series of methodologies. In 2013, they propose two methodologies to design the SM: the Analytical Hierarchical Process (AHP) (Quezada et al., 2013) and the Analytic Network Process (ANP) (Torres et al., 2013). The following year, they built up on these two methods and released new versions for AHP (Quezada & López-Ospina, 2014) and ANP (Quezada et al., 2014). They investigated the use of the combination of Decision making trial and evaluation laboratory (DEMATEL) and linear programming methodologies to build the SM in 2017 (López-Ospina et al., 2017) and the combination of ANP and DEMATEL methodologies in 2018 (Quezada et al., 2018). In 2019, they also investigated the design of SMs using a scenario approach (González et al., 2019) and fuzzy DEMATEL (Acuña-Carvajal et al., 2019). A year later, they did a study on the comparison of two SMs (one based on DEMATEL and the other based on experts) using cluster analysis (Moraga et al., 2020). Lastly, they explored again fuzzy DEMATEL in (López-Ospina et al., 2022) with a focus on selection of objectives and relationships. More recently, they combined ANP and Multi-objective Integer Optimization Model to identify causal relationships in a SM (Quezada et al., 2023). The researchers team also explored use of the BSC and SM to measure performance (Quezada et al., 2019), to prioritize strategic projects (Quezada, López-Ospina, et al., 2022) or to generate performance indicators (Quezada, Aguilera, et al., 2022).

The following Chapters of this thesis dissertation build upon this literature.

Part II – Center Piece

Chapter 1

Unveiling the Landscape of Strategy Maps

Foreword of Chapter 1

This first Chapter of the dissertation provides a complete overview of the literature on SMs and serves as the foundation for the subsequent Chapters (see Figure 1.1) by assessing the *knowledge base*, one of the two foundation pillars for designing an artifact with the DSR. This Chapter demonstrates the gaps that need to be filled in this literature and is a joint work with my PhD supervisor, Prof. Corentin Burnay and is associated to the finished paper entitled "*Rise of Data Analytics: Towards a New Era for Strategy Map Design? A Systematic Literature Review*".

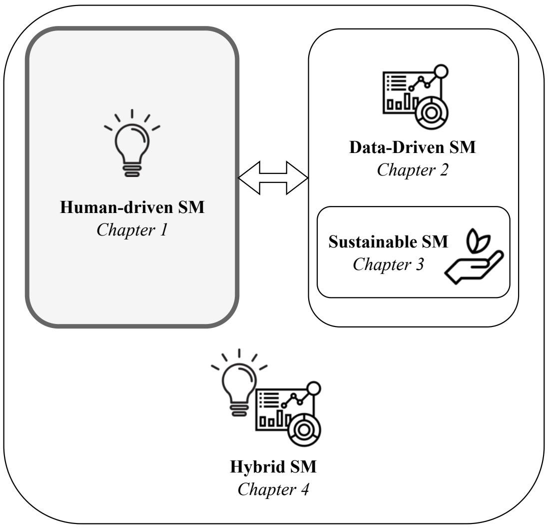

Figure 1.1: Positioning of Chapter 1 in the thesis

1.1 Introduction

Strategy is "*the long-term direction of an organisation*" (Johnson et al., 2020, p.4). It concerns the earliest, critical and complex questions any organization must answer; what long-term objectives should the organization achieve? How should it compete with other organizations? How will it remain prosperous and develop its activities? These questions require important decisions to be made. One influential tool to support such decisions is the BSC (Kaplan & Norton, 1992). When deciding about a strategy, the BSC stresses the importance of accounting not only for the financial dimension of the organization, but also the customer, internal business processes and learning and growth dimensions. The approach was then further developed with the introduction of the SM, a visual representation of the strategy (Kaplan & Norton, 2000) by means of causal links between its KPIs.

The definition of a strategy is likely to have a decisive impact on the success of an organization, mobilizing most of its resources and having a lasting influence on its functioning. Consequently, linkages between pairs of indicators in a SM bring many benefits to organizations. However, they are only valuable if they are validly identified and modeled. In practice, SMs tend to be developed based on the experts' knowledge and intuition of the organization – we call these "soft data" in the rest of the paper. Biases induced by human judgment have been studied in the cognitive psychology literature (Kahneman et al., 1982) as well as in the DM literature (Bazerman & Moore, 2012; Hastie & Dawes, 2009). Khatri and Ng (2000) found that intuitive processes, while often used in organizational DM, are negatively associated with organizational performance in a stable environment. Therefore, building long-term goals based on experts' knowledge and intuition may appear dangerous for the organization. Moreover, the absence of linkage validation in SMs has been pointed out as a serious mistake, e.g., Ittner and Larcker (2003) who suggest using data and data analytics to create such a tool.

On the other hand, technological advances are enabling organizations to collect, store, organize and analyze vast amounts of data. A paradigm shift has taken place and many organizations are becoming 'data-driven'. In other words, they are harnessing the power of data and the insights from analyzing their data for DM. Attempting to support the design of more robust SMs by mobilizing the potential of such data – we call these 'hard data' in the rest of the paper, as opposed to 'soft data' – through data analytics therefore seems a worthwhile endeavor, although our initial intuition is that theoretical and practical supports to do so are scarce.

The objective of this Chapter is therefore to investigate whether the ways to design SMs have changed in the age of data analytics. Traditionally, SMs linkages have been designed using soft data (Francioli & Cinquini, 2014). However, the rise of data analytics may have changed this. We carry out a Systematic Literature Review (SLR) on SM design. We put a specific focus on the types of methods and data leveraged in the practical design of SMs. Identifying what has already been addressed in SM design literature and highlighting existing gaps that require further investigation is crucial to improve the validity and robustness of such tools.

1.2 Background

1.2.1 The Strategy Maps

One of the most early, critical and complex question any organization has to answer is the question of its strategy; what long-term objectives should the organization achieve? How should it compete with other organizations? How will it remain prosperous and develop its activities? These are some essential questions which require important decisions to be made. One influential management theory to help making such decisions is the BSC developed by Kaplan and Norton in 1992 (Kaplan & Norton, 1992). When deciding about a strategy, the BSC stresses the importance of accounting not only for the financial dimension of the business, but also to think about the customer, internal business processes and learning and growth dimensions. The approach was then further developed in 2000 with the introduction of the SM (Kaplan & Norton, 2000), a visual representation of the strategy of an organization by means of KPIs, that is a *"set of measures focusing on those aspects of organizational performance that are the most critical for the current and future success of the organization"* (Parmenter, 2007).

In the SM, the KPIs of the organization are grouped in the 4 perspectives of the BSC and linked together in a cause-and-effect map. Cause-and-effect relations, also called *"causalities"*, associate KPIs within a same perspective or with KPIs located in a higher perspective, resulting in a fluid depiction of an organizational strategy. Figure 1.2 illustrates a generic SM, the arrows between the indicators representing the causalities.

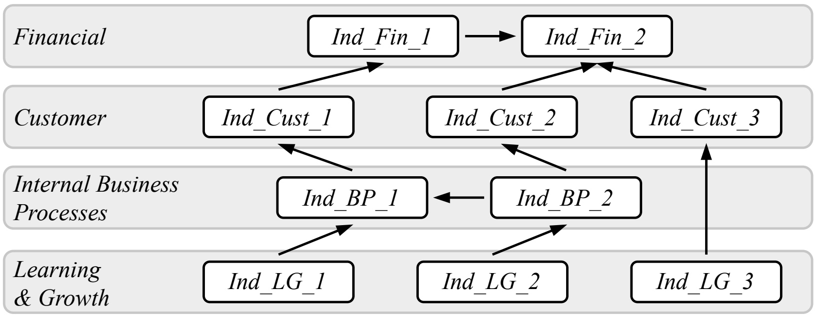

Figure 1.2: Representation of a simple generic SM

The principle of 'causalities' in SM has many advantages for organizations: it helps assessing the impact of DM on the rest of the company (or other KPIs), it provides guidelines to influence intangible KPIs using the predecessors as levers, it serves as a baseline for risk management, etc. It has also led the research community to explore various questions related to SM and its use in organizations (Kaplan & Norton, 2004), the role of SMs during strategy definition and deployment (Kádárová et al., 2015), the impact of SMs implementation on the organization's return on investment (Ittner & Larcker, 2003) or guidelines for creating SMs (see for instance Babar et al. (2010), Islam (2018), and Markiewicz et al. (2013)), among other things. Researchers have also advanced many propositions about how to actually produce SMs; the causalities are indeed valuable to an organization only if they are properly identified and modeled. Despite the numerous contributions related to the development of SM, we find little agreement on the practical development of SMs. Existing approaches often differ, notably in terms of epistemology (what data an organization should use to produce the SM?) and methodology (how should an organization proceed to build the SM?). This heterogeneity in the approaches to develop SM comes with a risk of confusion; practitioners and researchers face uncertainty about the best/most common approach to implement SM, face difficulties to understand how, when and why to create an SM because they lack a holistic perspective on the question. Identifying what has already been addressed in SM development literature and highlighting existing gaps that require further investigation therefore appears to be a worthwhile endeavor.

The SM is a tool derived from the BSC, and extends the concept further by linking the KPIs into a causal map. Some authors refer to the SM as a second generation BSC (see for instance Lawrie and Cobbold (2004)) or as a BSC with causal linkages (see for instance Soderberg et al. (2011)). The SM creates a visual representation that helps understanding the effect of change in preceding indicator on the following ones. The concept of cause-and-effect is essential for distinguishing a SM from other performance measurement scorecards (Kaplan & Norton, 2000).

Developing a SM is essential; it has been shown in the literature that not mapping KPIs correctly (i.e., not designing a SM to relate them) can be more detrimental to the organizations than not using those KPIs at all (Ittner & Larcker, 2003). These two authors argue that not linking KPIs nor validating their causalities is the cause of failure of performance models such as the BSC. They also find out that organizations that successfully achieve to build and verify their SMs experience higher returns on investments and returns on equity. Various motives for the use of the SMs (and BSCs) have been highlighted in the literature. For instance, companies can use the tools in order to formulate, control (Malina et al., 2007) and communicate (Kasperskaya & Tayles, 2013; Ritter, 2003) their strategy. Additionally, managers may use BSCs and SMs as tools with the purpose of DM and decision-rationalizing (Wiersma, 2009). In Cheng and Humphreys (2012), it is also showed that the SMs have a decision-facilitating impact for the managers as the causal linkages present in the model help them both to judge the relevance of external information as well as to evaluate if a strategy is appropriate. Even in nonprofit organizations, managers use the performance information comprised in such models for making decision (LeRoux & Wright, 2010).

In this review, we leave aside the reflexive tasks of defining the mission and vision of the organization and focus on the practical part of developing SM which we divide into three phases: the KPIs selection, the causality estimation and the causality validation. We insist on the distinction between causality estimation and validation, considering that among the companies which create a SM, only a small number pursuit to validate it (Ittner & Larcker, 2003). Each of these stages can be carried out using different types of methods (qualitative, quantitative or mixed) which can be based on different types of data (hard, soft or mixed). We use the term *soft data* for any data sourced from human beliefs, even when quantified, as opposed to *hard data* sourced from objective measures. Usually, defining causalities in the SMs are defined using soft data (Francioli & Cinquini, 2014), it has been the most investigated stage in the BSC or SM literature, and important limitations have been highlighted over the years (Nørreklit, 2000) and have been responded by supporters (Bukh & Malmi, 2005). Despite all these discussions, the BSCs and SMs remain mainstream approaches and it is still highly relevant to contribute on this question. Each stage is described hereafter:

- The *selection of KPIs* is an important step and has received significant attention in the literature. Indeed, not selecting the performance measures linked to the strategic goal is one of the common mistakes underlined by Ittner and Larcker (2003). KPIs' selection is a critical step that implies a trade-off regarding the optimal number of measures to include; designers should integrate enough KPIs so as to guide decision-makers properly but not many in order to avoid overloading the SM and make it an inefficient decision support tool. Different techniques exist to choose a reduced number of KPIs to include in the BSC before the linkage in the SM. Reducing the number of metrics in the map allows to have a clearer view of the strategy for the practitioners and avoid the company to lose focus on its strategy (Quezada et al., 2009). The choice of measures has been pointed out by Malina and Selto (2004) as critical and require to be adaptable to current conditions;

- The *causality estimation* between KPIs is the second stage. It is the method used to establish links between the different performance measures within the SM. The linkage characteristic of the SM makes it belong to causal performance measurement model and differentiates it from classic ones;

- The last stage in SM development is the *causality validation*. It represents the test of the previously established links between indicators following a causality estimation stage or by testing a theoretical model.

Although the SM has been introduced two decades ago and the quantity of contributions dealing with it is significant, there is surprisingly very few attempts to review and synthesize all the findings related to SM development. To the best of our knowledge, only one study (Islam, 2018) has been carried out with close topic. It reviews documents to provide guidelines for SMs development for practitioners. While this study is essentially normative, our Chapter focuses on the positive view of SMs development. Another distinctive point regards the contribution target; although both papers aim at both practitioners and researchers, the study of Islam (2018) has a greater impact for practitioners while our own review is rather intended to researchers. Moreover, the author does not follow a systematic review protocol for his study. The paper identifies 14 principles for developing SM based on 7 features and highlights the lack of empirical research on most of the presented features.

The previous section points out that the BSC is the predecessor of the SM tool. As the two concepts of SMs and BSCs are closely related, we find relevant to integrate BSCs work in this section as well. With the exception of the last reference, the following reviews are not systematic. One literature review (Hoque, 2014) investigates elements such as research topics, methods, contributions and research gaps but focuses on the BSC, which does not contain causalities. A review of the methods for building BSCs have also been addressed in Asgari and Darestani (2017). However, they restrict their analysis to the study of multi-criteria decision making methods only and discard other methods. Another paper reviews the literature on aspects linked with the evolution, usefulness and implementation of the BSC (Banchieri et al., 2011). The usefulness of BSC implementation is an issue that is a similar to the reasons and motivations to build a SM that will be investigated in our Chapter. Lastly, a systematic literature review has been conducted on the benefits of the SM for successful implementation (Lueg & Julner, 2014).

1.2.2 Data analytics

Data analytics is defined by Runkler (2020, p.2) as "*the application of computer systems to the analysis of large data sets for the support of decisions*". There are three types of data analytics: descriptive, predictive and prescriptive (Delen & Ram, 2018). Even though each type of analysis has a different purpose, the larger aim of data analytics is to help making sense of data. data analytics comprises a set of methods used to retrieve useful information from the data after it has been stored, extracted, transformed and loaded (Duan & Xiong, 2015). Data analytics is mostly conducted using hard data and quantitative methods and relies on quantitative statistical analysis methods such as econometric techniques, operations research methodologies. While the term quantitative methods, as opposed to qualitative, is widely used, we make a second distinction reflecting the source of the data: soft and hard. In this Chapter, we use soft data to refer to any data that comes from experts' knowledge and intuition, even if quantified, as opposed to factual hard data resulting from business operations and gathered in systems such as Business Intelligence or Decision Support Systems.

When applied to business data, to support fact-based organizational DM, data analytics can be referred to as Business Analytics (Davenport & Harris, 2017). Although high-performing organizations use more analytics than intuition (LaValle et al., 2011), many criteria restrict the use of data analytics in organizations such as the lack of analytic talents, the corporate culture, fear of poor return on investment, data itself, the available technology and the security and privacy of the data (Delen & Ram, 2018). At the operational level, data analytics allows seizing business opportunities such as the identification of new customer segments or the clarification of sales seasonality among other things (Russom, 2011). Business analytics is agnostic as to the industry sector and can be applied to any department of an organization such as supply chain or human resources (J. Yin & Fernandez, 2020). However, few papers explore the use of data analytics at a strategic level, for strategy design or strategy development. For instance, the value of business analytics in performance management tools has been explored and it has been proposed to validate the causal relationships present in SMs (Schläfke et al., 2013). Nevertheless, this remains at the research proposal step. This brings the central question of our Chapter: *has the design of SM evolved in the age of Data analytics?*

1.3 Methodology

In this Chapter, we adopt the SLR methodology which allows "*a fair evaluation of a research topic by using a trustworthy, rigorous, and auditable methodology*" (Kitchenham & Charters, 2007, p.iv). We perform this SLR following the recommendations and protocol of Webster and Watson (2002) and Kitchenham and Charters (2007) (Figure 1.3). This protocol is essential to document the whole process, guide and organize the SLR (Vom Brocke et al., 2015) and diminishes potential bias making the review more transparent and replicable (Kitchenham & Charters, 2007). Those steps will constitute the following subsections: research questions, inclusion and exclusion criteria, the search procedure and study selection, and data extraction. While the analysis of our sample of documents will be carried out in the following section.

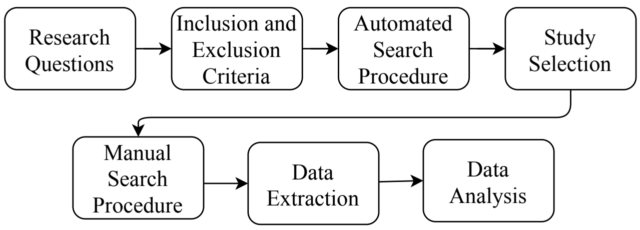

Figure 1.3: Systematic literature review framework

1.3.1 Research questions

The definition of research questions helps guide the review process and determine our inclusion and exclusion criteria. We develop three research questions (RQs). The first reports the state-of-the-art of SM design: **RQ1** – "*How did the literature about SMs design evolve over the past two decades?*". The second investigates the methods used to design SMs: **RQ2** – "*What are the trends in terms of methods and methodology types for strategy maps design?*" This RQ examines how SMs have been developed in the literature by classifying the research methods and determines when those methods appeared and are carried out over time. The last RQ examines the type of data (hard, soft or mixed) used to design SMs: **RQ3** – "*What are the trends in terms of data sources for strategy maps design?*"

1.3.2 Inclusion and exclusion criteria

The second step consists in defining the inclusion and exclusion criteria for our SLR. The inclusion and exclusion criteria are inserted in the search procedure, through settings to set boundaries to our study (Webster & Watson, 2002) and to target the right papers while not being overwhelmed by the amount of papers in the literature as this has become one of the main challenge in literature reviews (Vom Brocke et al., 2015).

- *Publishing date*: the linkage intuition in the BSC started earlier than the SM formalization in 2000. For instance, Kaplan and Norton already mentioned linking the different perspectives and measures in 1996 (Kaplan & Norton, 1996). Starting in 1992 – the year of creation of the BSC – would ensure that we capture all papers related to SMs;

- *Document type*: we limit our review to documents from peer-reviewed articles, conference papers and reviews. Books and book Chapters mainly focus on theoretical approaches to the concept and are not part of the scope of our study. We did not include criteria on journals' fields because this type of research is applicable to a lot of fields and it would limit our paper retrieving;

- *Language*: to carry on a proper analysis and comparison, we limit our review to English written documents.

Table 1.1 summarizes the inclusion and exclusion criteria defined for our study.

	Inclusion criteria	**Exclusion criteria**
Document type	Articles, Conference papers, Reviews	Books/book Chapters, Thesis dissertations Technical reports, Editorials
Publishing date	From 1992 to this day	Before 1992
Language	Published in English	Other languages

Table 1.1: Study inclusion and exclusion criteria

1.3.3 Search procedure and study selection

We combine an automated and a manual search to ensures to extract all the relevant documents and make this SLR more reliable and unbiased.

Automated search

We carry on an automated search which enables to extract a large quantity of papers coming from several databases thanks to a query. We include both *'balanced scorecards'* and *'strategy maps'* as keywords in our search query as many researchers consider the SM development as part of the creation of a BSC and use the two terms interchangeably. However, we retrieve papers with *'balanced scorecard'* keywords only when associated with *'linkage'* keyword in order to avoid all papers that are out of the scope of our review. The search query, settings and five chosen databases are presented in Table 1.2. The inclusion and exclusion criteria are taken into account in the search settings and filters of the databases: publication year, document type and document language. The final query was run against a total of five databases which are listed in Table 1.2. The search target was the abstracts of the documents in order to have the search procedure normalized among all five databases. The last automated search has been performed in May 2021.

Search terms	(“strategy maps” OR “strategy map” OR (“balanced scorecards” AND linkage) OR (“balanced scorecard” AND linkage))
Search settings	Date: since 1992 Language: English Document type: articles, conference papers and reviews
Databases	Scopus, EBSCO Host, IEEE Xplore, Wiley Online Library, Emerald Insight

Table 1.2: Automated search procedure

First screening and quality assessment

Before quality assessment, a first screening is performed with the analysis of the title and abstract of the papers for the automated search. Indeed, the keyword search can lead to papers that are not related to our topic of interest. We retain the documents that positively answer the following question: *“Does the document present a practical development a SM in the sense of Kaplan and Norton?”* This allowed us to exclude conceptual papers as well as other uses of ‘strategy map’ name referring to other concepts.

Then, the retention of documents from the automated search is based on quality assessment. We objectively ensure the quality of our sample through a combination of external rankings. We define the quality of a document, and its eligibility to proceed further in the review, using multiple rankings of the source where the document is published. Indeed, we are interested in the development of SMs regardless of the field of application. Journal and conferences rankings are usually defined by field and vary according to the specification of the listing, thus we combine several rankings for the quality assessment. We decide to keep a document if it has been published in a high-quality journal or conference according to at least one of the rankings. Table 1.3 shows the quality level that needs to be attained in order to proceed further in our review.

The documents from low quality journals and conferences are removed from the review. A total of 73 papers are withdrawn ensuing the quality assessment procedure. All documents removed after quality check are

Journal articles		Conference papers	
Ranking	*Selected if equal to or above*	*Ranking*	*Selected if equal to or above*
SJR	Q1, Q2	SJR	12 H-index
CORE	A*, A, B	CORE	A*, A, B
CNRS	rank 1, rank 2	ERA	A, B
		QUALIS	A1, A2, B1, B2

Table 1.3: Rankings for quality assessment

stored in a separate file. We retain 48 journal papers and 10 conference papers for a total of 58 documents that can proceed further to the manual search.

Manual search

We apply a manual *backward* search after the quality check with the intention to extend the number of papers extracted by detecting additional papers. The backward search is a snowballing approach (Wohlin, 2014) which identifies papers parencited in the reference list of the retained papers from the automated search. This manual search adopts the same inclusion and exclusion criteria presented in the previous section.

The manual search is carried out by analyzing the title of the documents parencited and retain to ones comprising the words "*Strategy Map(s)*" or "*Scorecard(s)*" as a first selection. Then, the decision to retain the new documents is made based on the abstract. After the paper is selected, it has to go through to the quality assessment process in order to integrate it in the sample list of documents for the review. The manual search allowed us to retrieve 23 documents that were not identified by the automated search and a number of 17 papers could be added to our documents' sample for the review.

Search results

A total of 75 documents results from the previous steps which will go through data extraction and analysis. Figure 1.4 shows of the number of documents retained at each step of the procedure. For the sake of transparency, the complete list of extracted documents for our review has been published and can be accessed online[1]. All documents from our sample are summarized in Table 1.11 in Appendix 1 of this Chapter.

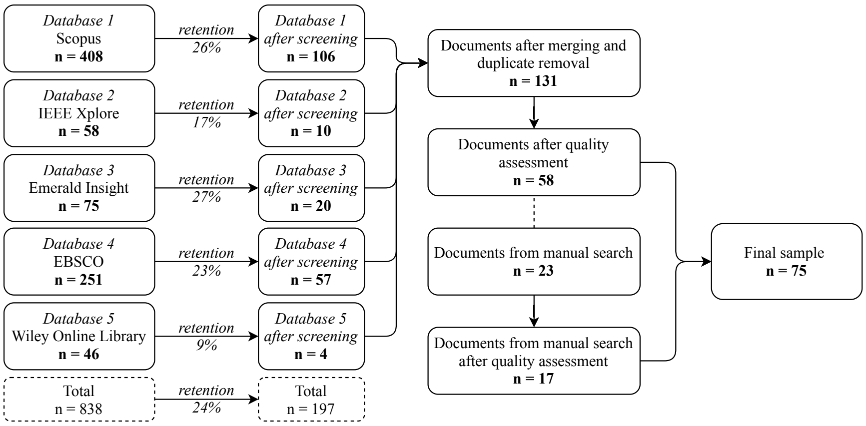

Figure 1.4: Automated and manual searches result

1.3.4 Data extraction

Before the analysis of our sample, we extract the information contained in the documents. The information is stored in a data extraction matrix in order to be systematic in our analysis and ensure the reliability of our review. This matrix captures information about the papers along with specific items that enables us to address each research question. In order to facilitate the data analysis procedure, we predefined several items to extract information. The theme of each study should be selected from the three steps of the development of SMs discussed earlier in this Chapter, namely *KPI selection*, *linkage estimation* and *linkage validation*. Similarly, the methodology type of the paper should be picked from the following list: *quantitative*, *qualitative* or *mixed*. Finally, the study objectives are derived from the literature and should be one among: *planning*, *communication*, *control*, *alignment* or *other*. The type of data used in the development of SMs can be qualified as *hard*, *soft* or *mixed* based on its source. Lastly, the categories representing the type of

[1]doi.org/10.17632/fkk5g48ksw.1 (Pirnay & Burnay, 2021b)

organization are identified post hoc. The complete list of data extraction elements and corresponding description summarized in Table 1.4.

Elements	**Description**
ID	Identifier of the study
Author(s)	Name of the author(s)
Title	Title of the paper
Year	Publication years of the document
Country	Country of affiliation of the corresponding author
Source Name	Name of journal or conference in which the document is published
Citations	Number of citations to the day of extraction
Document type	Journal article or conference paper
Study type	Type of study of the document
Study theme(s)	*Indicator selection*, *causality estimation* or *validation*
Methodology type	*Qualitative*, *quantitative* or *mixed* methodologies
Method(s)	List of the paper's method(s) to develop a SM
Data type	Type of data analyzed: *hard*, *soft* or *mixed*
Study objective(s)	Motivations for the SM development
Organization type	Type of organization for which the SM is developed
Findings	Description of the findings

Table 1.4: Data extraction matrix

1.4 Results

In this section, we answer the three research questions developed in subsection 1.3.1.

1.4.1 Evolution of the SMs literature (RQ1)

This subsection analyzes the 75 documents resulting from the previous procedure. Only 11 out of the 75 selected papers are conference papers and the 64 other documents are published in scientific journals. In total, 71 documents include a case study (95%), 32 follow a methodological proposition and 39 have applied case study only. It is quite rare to encounter a document with a methodological proposition which is not tested with a case study (5%) (Figure 1.5).

Figure 1.6 presents the distribution of documents between 2001 and 2021 and we observe a general positive trend on the publication of journal

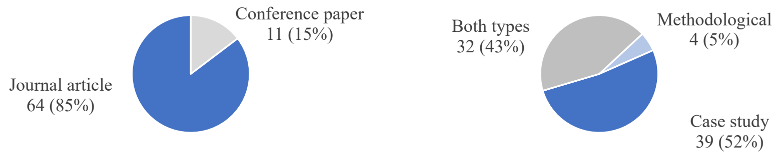

Figure 1.5: Documents and study types

articles and conference papers during this period. Although the research query started in 1992 in order to include BSC with causal linkages, we observe that the first document of our sample has been published in 2001. Since this year, there is at least one published document every year until 2021 that concerns SM development. The SM concept was developed in 2000 and it has taken a couple years for the researchers to start publishing on this subject. We can clearly state that the second decade is the busiest period for publications of SM development with three quarters of the total number of documents published between 2011 and 2021, the busiest years are 2011 and 2018 with respectively a total of 10 and 8 documents. This also suggests a relative maturity of the field on this question, and further motivates our review.

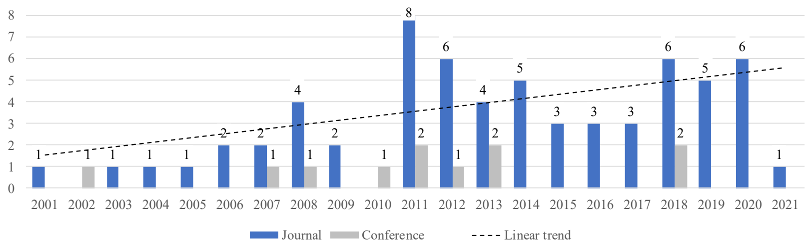

Figure 1.6: Number of documents per year

Table 1.5 illustrates the geographical distribution of the selected documents as well as the number of citations divided by the number of documents of each country of our sample. The country of affiliation of the document's corresponding author has been used to describe the geographical characteristics of our sample. Surprisingly, while the SM concept was created by two Americans authors, only two documents are attributed to the United States of America. Another noticeable result is the number of documents published by Iranian (15) and Taiwanese (8) authors. Together, these two countries represent more than 30% of our final sample. One possible explanation for that could be the research interest of one research team in a specific University or the venue of a conference on SM/BSC or similar topic. It is also important to note that the 'countries' presented in the Table correspond to the country of affiliation of the main authors and does not reflect the country of publication source nor the country of other authors whether the main author collaborated with external colleagues. These analyses could yield different results.

Country	**Number of documents**	**Country**	**Number of documents**
Iran	15	Austria	1
Taiwan	8	Brazil	1
Chile	5	Canada	1
Greece	5	Finland	1
India	4	France	1
Italy	4	Germany	1
China	3	Israel	1
Colombia	3	Lithuania	1
Portugal	3	Thailand	1
Spain	3	Turkey	1
Indonesia	2	UAE	1
Russia	2	UK	1
USA	2	Venezuela	1
Australia	1	Vietnam	1

Table 1.5: Distribution of documents and citations by country

Looking at the geographical repartition of the documents by region (Figure 1.7), European and Asian regions are the most represented in the SM development publications with 21 documents each between 2001 and 2021.

Table 1.6 presents the five journals that are the most represented in our sample of documents (see Appendix 2 of the present Chapter for the full list of document sources). Unfortunately, this analysis is not relevant for our documents sourced from conferences due to the small number of conference papers retrieved in our final sample. The most

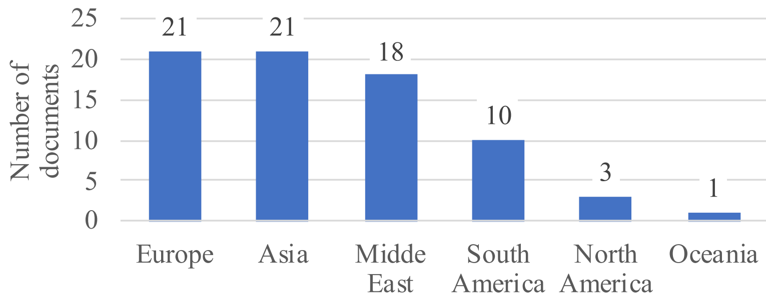

Figure 1.7: Distribution of documents per regions

active authors in terms of number of documents (journal and conference papers combined) published is presented in Table 1.7.

Journal name	**Number of documents**
International Journal of Productivity and Performance Management	6
Expert Systems with Applications	5
International Journal of Production Economics	4
Journal of Cleaner Production	3
Management Decision	3

Table 1.6: Top 5 of journals in our final sample

We analyze the companies of the case studies in terms of sectors and types then we focus on the motivations behind the SM development. We examine here only the 71 documents of our sample containing a case study. Figure 1.8 presents the full distribution of the case studies among the different sectors. We notice that 7 case studies did not specify the company type the data was used from and were marked as *"Not specified"* in our analysis. The educational sector is the most represented sector (13%), followed by the banking sector (10%) and then, equally, the public, medical and automotive sectors (8% each). It is not surprising that the educational sector, mainly composed by universities, is the most represented among the case studies. Indeed, the researchers have easily access to this type of data.

Author name	Number of documents
L. E. Quezada	7
P. I. Palominos	5
H. A. López-Ospina	4
M. Gykas	4
R. A. Barros-Castro; P. Chytas; A. Cugini; S. Farokhi; J. Jassbi; F. Mohamadnejad; A. M. Oddershede; E. Roghani; G. Valiris	2

Table 1.7: Top 5 of authors in our final sample

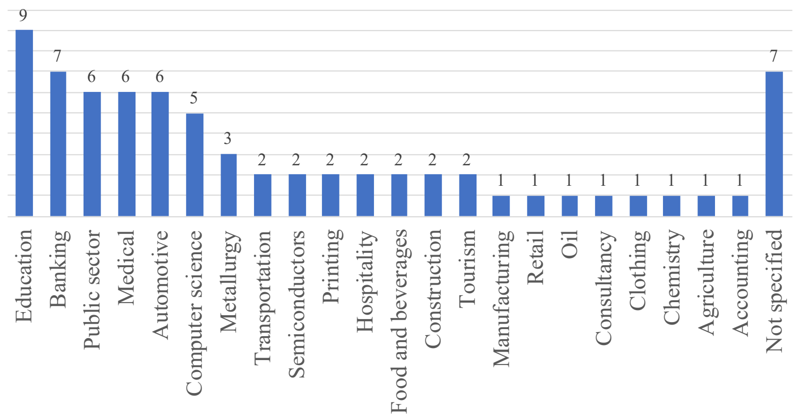

Figure 1.8: Number of case studies by sectors

In the literature, common motives for developing SMs have been highlighted namely: formulation, planning, communication, control and alignment. In this review, we notice that among the motivations proposed in the literature, formulation, planning and control are the main drivers for building a SM in a company (Figure 1.9). However, 29 documents also mentioned other reasons to develop the SM, for instance, to identify critical areas of a business, to coordinate cross-organizational processes, to position themselves in relation to the competitors, to measure the level of performance or to improve the quality of a process, among others. Lastly, 7 case studies (10%) have the only purpose of testing the methodology proposed by the authors.

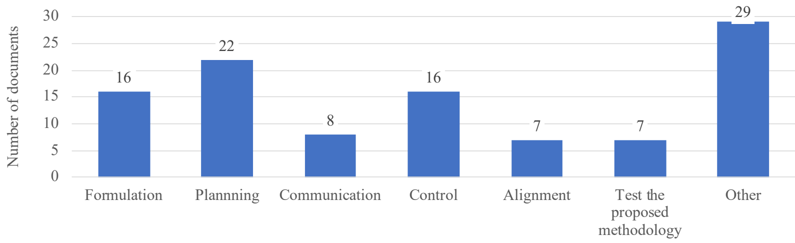

Figure 1.9: Motivations behind SM building

Our data extraction allows to analyze the type of organizations of the case studies. Specificities associated with the company type can have an impact on the SM developed which makes this analysis relevant in our review. Only 8% out of the 71 documents presenting a case study are related to small and medium-sized enterprises and only 17% investigate the case of non-profit organizations (Figure 1.10).

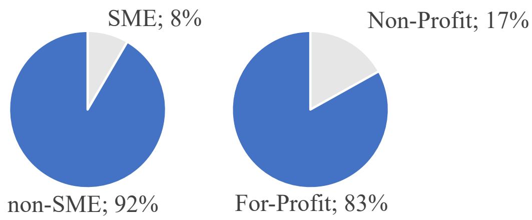

Figure 1.10: Case studies investigating SMEs or Non-profit organizations

1.4.2 Trends in research methods for SM design (RQ2)

Stage I: indicator selection

The selection of KPIs is the first practical step towards building the SM after defining the mission and vision of the company. Among the 75 documents analyzed, one third (24 documents) did not specify how they selected the indicators to put in the SM. In Table 1.8, we observe that the most represented method for selecting the indicators to integrate in the SM is *brainstorming*, *workshops* and *experts discussion*. *Literature review* is also well used for this stage of SM development. Those methods grow even more with the time. Interviews methods such as *in-depth interviews* seem to be constantly used over the years. Since 2011, after one decade of SM existence, other methods can observed such as (fuzzy) *Delphi* or *surveys*. Another interesting result shows that the indicators' selection methods that are not specified were representing one third of the total methods between 2001 and 2010 but this ratio has decreased since 2011 meaning that the scientific literature is more careful about specifying the methods they used for this stage then before.

Methods for selection stage	**2001-2005**		**2006-2010**		**2011-2015**		**2016-2021**		***Total***	
	%	*(n)*	*%*	*(n)*	*%*	*(n)*	*%*	*(n)*	*%*	*(n)*
Brainstorming, Workshops, Experts	3%	(3)	3%	(3)	10%	(9)	11%	(10)	27%	(25)
Literature review	.	.	2%	(2)	6%	(6)	11%	(10)	19%	(18)
Interviews	1%	(1)	2%	(2)	2%	(2)	2%	(2)	8%	(7)
Survey	.	.	.	.	4%	(4)	1%	(1)	5%	(5)
SWOT	.	.	.	.	4%	(4)	.	.	4%	(4)
Secondary Data	.	.	1%	(1)	.	.	2%	(2)	3%	(3)
(fuzzy) Delphi	.	.	.	.	1%	(1)	2%	(2)	3%	(3)
Benchmarking	.	.	1%	(1)	1%	(1)	.	.	2%	(2)
System Thinking	.	.	1%	(1)	.	.	.	.	1%	(1)
Web Mining	.	.	.	.	1%	(1)	.	.	1%	(1)
Not specified	2%	(2)	5%	(5)	11%	(10)	8%	(7)	26%	(24)
Total % (n)	*6%*	*(6)*	*16%*	*(15)*	*41%*	*(38)*	*37%*	*(34)*		*(93)*

Table 1.8: Distribution of methods for indicators' selection stage over the years

Stage II: causalities estimation

The estimation of causal links between the indicators in the SM is the next step to develop the tool. Table 1.9 exhibits all the methods use for causality estimation in the 71 case studies of our sample of documents. A first interesting finding is the large number of distinct methods found in the documents - 27 in total - with many of them only use in a single document. We also observe that the most represented method is *Brainstorming* and *Experts Discussion* (13%) which has been constantly used throughout the two decades. The second most popular method is the *DEMATEL* (Decision Making and Trial Evaluation Laboratory) method (12%). This one can be adapted (*fuzzy-DEMATEL*) or combined with other methods such as *ANP* (Analytical Hierarchy Process) (7%)

and have only started to make appearance in the second decade since the SM concept was created. Taken all together, the DEMATEL method occurs 19% of the time. *Fuzzy Cognitive Maps* method is also well utilized in this stage of the SM building (7%). It is important to notice that all the previously mentioned methods are based on soft data. However, the methods are looking to quantify data and counter subjectivity with fuzziness from 2011 and on. Indeed, methods such as *Linear programming* and *Interpretative Structural Models*, among others, follow this trend. Another important result to notice is the number of documents that did not specify their methods for the causalities estimation (20%) is actually higher in the last decade than in the first one.

Methods for estimation stage	2001-2005		2006-2010		2011-2015		2016-2021		*Total*	
Brainstorming, Experts	3%	(3)	3%	(3)	2%	(2)	4%	(4)	*13%*	*(12)*
(fuzzy) DEMATEL	.	.	.	.	3%	(3)	9%	(8)	*12%*	*(11)*
Fuzzy Cognitive Maps	.	.	1%	(1)	4%	(4)	1%	(1)	*7%*	*(6)*
DEMATEL + ANP	.	.	.	.	3%	(3)	3%	(3)	*7%*	*(6)*
Interviews	.	.	2%	(2)	1%	(1)	1%	(1)	*4%*	*(4)*
Survey	.	.	1%	(1)	2%	(2)	1%	(1)	*4%*	*(4)*
System Dynamics	.	.	1%	(1)	2%	(2)	.	.	*3%*	*(3)*
Structural Equation Modeling	.	.	1%	(1)	1%	(1)	1%	(1)	*3%*	*(3)*
Linear Programming	.	.	.	.	1%	(1)	1%	(1)	*2%*	*(2)*
Literature review	.	.	.	.	2%	(2)	.	.	*2%*	*(2)*
Interpretative structural model	.	.	.	.	.	.	2%	(2)	*2%*	*(2)*
Causal Loop Diagram	.	.	1%	(1)	1%	(1)	.	.	*2%*	*(2)*
Dynamic simulation technique	1%	(1)	.	.	.	.	.	.	*1%*	*(1)*
Dynamic Data Mining	.	.	1%	(1)	.	.	.	.	*1%*	*(1)*
System Thinking	.	.	1%	(1)	.	.	.	.	*1%*	*(1)*
Strategy Trees	.	.	1%	(1)	.	.	.	.	*1%*	*(1)*
Analytical Hierarchy Process	.	.	.	.	1%	(1)	.	.	*1%*	*(1)*
Topology Mapping	.	.	.	.	1%	(1)	.	.	*1%*	*(1)*
Analytical Network Process	.	.	.	.	1%	(1)	.	.	*1%*	*(1)*
Fuzzy Inference Systems	.	.	.	.	1%	(1)	.	.	*1%*	*(1)*
Fuzzy network	.	.	.	.	.	.	1%	(1)	*1%*	*(1)*
Strategic value chain	.	.	.	.	.	.	1%	(1)	*1%*	*(1)*
SWOT	.	.	.	.	.	.	1%	(1)	*1%*	*(1)*
Decomposition Approach	.	.	.	.	.	.	1%	(1)	*1%*	*(1)*
Intuitionistic Fuzzy Sets	.	.	.	.	.	.	1%	(1)	*1%*	*(1)*
Fuzzy Logarithmic Least Squares	.	.	.	.	.	.	1%	(1)	*1%*	*(1)*
Not Specified	1%	(1)	3%	(3)	9%	(8)	7%	(6)	*20%*	*(18)*
Total % (n)	*6%*	*(5)*	*18%*	*(16)*	*38%*	*(34)*	*38%*	*(34)*		*(89)*

Table 1.9: Distribution of methods for causality estimation over the years

Stage III: causalities validation

The validation of causal links between the indicators of the SM, following their estimation, is relatively scare in the literature of SM development. Indeed, only 13 papers (17,3%) of the selected documents pursue to validate the causalities they estimate. We observe that the methods are very scattered and represented only once except for the *Experts Discussion* which appears four times between 2011 and 2021 (see Table 1.10).

Methods for validation stage	**2001-2005**		**2006-2010**		**2011-2015**		**2016-2021**		***Total***	
Experts	.	.	.	.	7%	(1)	20%	(3)	*27%*	*(4)*
Survey	.	.	7%	(1)	.	.	.	.	*7%*	*(1)*
Structural Equation Modeling	.	.	7%	(1)	.	.	.	.	*7%*	*(1)*
Analytical Network Process	.	.	.	.	7%	(1)	.	.	*7%*	*(1)*
Linear Programming	.	.	.	.	7%	(1)	.	.	*7%*	*(1)*
Response Surface Methodology	.	.	.	.	7%	(1)	.	.	*7%*	*(1)*
Monte Carlo Simulation	.	.	.	.	7%	(1)	.	.	*7%*	*(1)*
Multivariate Regression	.	.	.	.	.	.	7%	(1)	*7%*	*(1)*
Artificial Neural Networks	.	.	.	.	.	.	7%	(1)	*7%*	*(1)*
Dynamic Data Mining	.	.	.	.	.	.	7%	(1)	*7%*	*(1)*
Simultaneous Equations System	.	.	.	.	.	.	7%	(1)	*7%*	*(1)*
Analytical Hierarchy Process	.	.	.	.	.	.	7%	(1)	*7%*	*(1)*
Total % (n)	.	.	*13%*	*(2)*	*33%*	*(5)*	*53%*	*(8)*		*(15)*

Table 1.10: Distribution of methods for causalities validation stage over the years

1.4.3 Data sources used for SM design (RQ3)

As shown in Figure 1.11, the totality of the papers that specified the indicator selection method are using soft data. Indeed, no document is using hard or mixed data for this stage of the SM development. Qualitative methods are the most used research methods with 86% of the covered documents. Mixed (8%) and quantitative (6%) methods are poorly represented for the selection of indicators.

By looking at Figure 1.11, we still observe a predominance of soft-data type for this causality estimation stage (86%). The methods are either qualitative or quantitative but seldom mixed. We can also notice that some documents carry out qualitative or quantitative methods with mixed data and a few used hard-data quantitative methods. In Figure 1.11, we also notice that we have a majority of quantitative methods (62%) from this stage of causalities validation compared to the two preceding steps. We still have a considerable number of methods based on soft data either with qualitative (31%) or quantitative (23%) methods. However, we have 31% of the methods characterized as hard data quantitative methods. We can also observe a few documents carrying out hard-data qualitative and mixed-data quantitative methods while none of the 13 documents apply a mixed method. Regarding the analysis of the methods and data source types for the three stages combined, Figure 1.11 shows that, overall, the soft-data mixed method and soft-data qualitative methods are the most carried out. Purely quantitative methods are also represented, mostly when using soft data source. While there are no hard-data quantitative methods at all, the other combination are scarce.

Indicators selection stage

	Qualitative Methodology	Mixed Methodology	Quantitative Methodology
Soft Data	86%	8%	6%
Mixed Data	0%	0%	0%
Hard Data	0%	0%	0%

"Not specified": 24

Causalities estimation stage

	Qualitative Methodology	Mixed Methodology	Quantitative Methodology
Soft Data	39%	4%	47%
Mixed Data	2%	0%	4%
Hard Data	0%	0%	5%

"Not specified": 18

Causalities validation stage

	Qualitative Methodology	Mixed Methodology	Quantitative Methodology
Soft Data	31%	0%	23%
Mixed Data	0%	0%	8%
Hard Data	8%	0%	31%

Documents with validation: 13

All-stages

	Qualitative Methodology	Mixed Methodology	Quantitative Methodology
Soft Data	38%	35%	12%
Mixed Data	1%	9%	1%
Hard Data	0%	1%	3%

"Not specified": 6

Figure 1.11: Methodology and data types

1.5 Discussion

Our review reveals an important gap in the design of SMs. Indeed, very little work has attempted to integrate data analytics in the design of SMs as shown by the poor proportion of hard data quantitative methods in the design process of the SMs. These results are important because the heavy use of experts' knowledge and intuition in the design of such strategic tools comes with important risks for the prosperity of any organization, as it can lead to strong biases in the tools. Moreover, our study points out three major shortcomings and allows answering the question "*Has the design of SM evolve in the age of data analytics?*":

- **The lack of hard-data based methods for designing strategy:** our review of the literature has shown that hard data-based methods are underrepresented in the design of SMs, although we can note that efforts have been made at the level of methods to counteract the subjectivity introduced by humans into the process (we observe more fuzzy and quantitative methods over time). The use of soft data in the context of SMs can lead to accuracy issues, incompleteness and poor longitudinal perspective (Pirnay & Burnay, 2021a). Researchers could direct their future research toward the use of hard data to develop SMs, regardless of the type of method used. Since the democratization of information systems, organizations can collect and store a lot of data in their databases. These hard data are already used for many business purposes such as marketing (Shah & Murthi, 2021) and human resources (Nocker & Sena, 2019), among others. With a small investment, organizations could use these databases to perform multiple steps of the SM design;

- **The lack of validation of causal links between the indicators:** a second gap highlighted by our review concerns the small number of papers that pursuit the validation of the causal relationships they introduce in their SMs after their estimation. In fact, only 17% of all case studies in our sample validate the linkages they put in the SM tool. The importance of validating the causal links between the indicators of a SM has already been discussed in the literature (Ittner & Larcker, 2003) and should be considered as an important step in the construction of the tool. We advise researchers to investigate the validation of linkages in the SM. We recommend investigating the methods that can be used to validate linkages and the impact of this step on the organization's SM. Several authors have already given leads for the validation of these linkages using hard data with Structural Equation Modeling (Sadeghi et al., 2013; Slapničar & Buhovac, 2014) or at least an evaluation by the experts of the organization;

- **The lack of methodology specification:** Our SLR summarizes the state-of-the-art of the literature and highlights important gaps presented in the previous Section. We have noticed that many papers omitted to mention the methods used to develop one or more stages of SMs. It is relevant to highlight this phenomenon, which has mostly worsened in recent years, as the type of methods used is investigated in this study but is also significant for the field as it does not help (i) researchers to position their work in this literature and (ii) practitioners to learn from good practice from the literature.

Although the SLR procedure increases reliability, we point out three major limitations that threaten the validity of our review. First, our final sample and analyses depend heavily on the choice of keywords for the search query and on the choice of the five databases for the document search. Other keywords might have retrieved other relevant papers. Second, the snowballing method for the manual search was applied only to the title of the references. Again, we might have missed some relevant papers that do not mention "Balanced Scorecard" or "Strategy Map" in their title. Finally, although all authors participated in the extraction of data from the papers used to investigate the research questions of this study, it is prone to subjectivity biases. We addressed this issue by using an extraction matrix to make information extraction systematic. Despite the limitations of our study, we present avenues for further research on this topic. The first research direction that stems from this article is the practical exploration of the room for data analytics in SMs design. As we have demonstrated that applying data analytics in the design process of SMs is indeed relevant, it is now time to develop new frameworks for designing data-driven SMs. For instance, a proposed framework already explores the use of vector auto-regression models on hard data to design SMs (Pirnay & Burnay, 2022). A second research direction that arises from our research is to extend this study to other strategic or performance tools.

1.6 Conclusion

Designing organizational strategies is a critical task that requires careful consideration and planning. Over the past two decades, tools such as the SM have been developed to aid in this process. The aim of this SLR is to analyze the practical design of the SM tool since its creation and explore whether it has changed in the age of data analytics by examining trends in methods and data types. We developed three research questions that address (i) the general evolution of the SM literature, (ii) the trends in SM design methods, and (iii) the trends in SM design data sources. Our sample consists of 75 journal papers and conference papers.

The analysis revealed that although the SM is not a new tool, it is still receiving significant attention from the research community. However, the methods used to create SMs tend to be mostly qualitative for selecting KPIs, qualitative and quantitative for estimating linkages, and mostly quantitative for validating linkages. It was found that very few case studies perform the validation of linkages between the KPIs of the map. Additionally, soft data was found to be the predominant type of data source used to create SMs, even for quantitative methods. This suggests a need for more hard data-based methods and frameworks to be integrated into the practical and theoretical design of SMs. There is a need for causal relationship validation to ensure the accuracy and validity of the linkages between KPIs. In conclusion, while the SM has been around for over 20 years, there is still much room for improvement. By addressing these previously mentioned shortcomings, SMs can be improved and become an even more valuable tool for organizations in designing their strategies.

1.7 Appendices of Chapter 1

Appendix 1 – Final sample of documents for the SLR

In-text citation	Document Type	In-text citation	Document Type
Acuña-Carvajal et al. (2019)	Journal	Mair (2002)	Conference
Ahn (2001)	Journal	Mendes et al. (2012)	Journal
Amado et al. (2012)	Journal	Mohamadnejad and Jassbi (2012)	Conference
Asli et al. (2013)	Journal	Moraga et al. (2020)	Journal
Balkovskaya and Filneva (2016)	Journal	Nauhria et al. (2018)	Journal
Barnabè (2011)	Journal	Okongwu et al. (2015)	Journal
Behery et al. (2014)	Journal	Ostadi et al. (2020)	Journal
Bianchi and Montemaggiore (2008)	Journal	Papalexandris et al. (2004)	Journal
Chan (2009)	Journal	Papenhausen and Einstein (2006)	Journal
Chen et al. (2011)	Journal	Pérez Hoyos (2018)	Conference
Chou and Li (2011)	Conference	Quezada and López-Ospina (2014)	Journal
Chytas et al. (2008)	Conference	Quezada et al. (2014)	Journal
Chytas et al. (2011)	Journal	Quezada et al. (2018)	Journal
Cugini et al. (2011)	Journal	Rabetino et al. (2017)	Journal
de Andrade et al. (2018)	Journal	Rezaee et al. (2021)	Journal
De Carlo et al. (2008)	Journal	Rodpai and Hong-ngam (2020)	Journal
Dror (2007)	Journal	Rosmansyah et al. (2011)	Conference
Duarte and Cruz-Machado (2015)	Journal	Sadeghi et al. (2013)	Journal
Falle et al. (2016)	Journal	Sayed and Lento (2018)	Journal
Farokhi and Roghanian (2018)	Journal	Serdar Asan and Tanyaş (2007)	Journal
Farokhi et al. (2019)	Journal	Seyedhosseini et al. (2011)	Journal
Glykas (2012)	Journal	Silvestro (2014)	Journal
Glykas (2013)	Journal	Solano et al. (2003)	Journal
González et al. (2019)	Journal	Tejedor et al. (2008)	Journal

Groene et al. (2009)	Journal	Thanki and Thakkar (2018)	Journal
Hsu et al. (2011)	Journal	Tizroo et al. (2017)	Journal
Huang et al. (2006)	Journal	Tohidi et al. (2010)	Conference
Huynh et al. (2020)	Journal	Tsai et al. (2020)	Journal
Jafari et al. (2015)	Journal	Umayal Karpagam and Suganthi (2012)	Journal
Jassbi et al. (2011)	Journal	Urrutia and Eriksen (2005)	Journal
Kala and Bagri (2016)	Journal	Valmohammadi and Servati (2011)	Journal
Khakbaz and Hajiheydari (2015)	Journal	Wu (2012)	Journal
Khanmohammadi et al. (2019)	Journal	C.-H. Yang and Lee (2020)	Journal
Kunc and Morecroft (2010)	Journal	Y. Yang et al. (2013)	Conference
Leksono et al. (2019)	Journal	Yu and Wang (2007)	Conference
Li et al. (2013)	Conference	Zhang and Huang (2012)	Journal
López-Ospina et al. (2017)	Journal	Zolfani and Ghadikolaei (2013)	Journal
Lukmanova et al. (2018)	Conference		

Table 1.11: Sample of documents

Appendix 2 – Complete list of journals and conferences

Publishing source	**Source type**	**Number of documents**
International Journal of Productivity and Performance Management	Journal	6
Expert Systems with Applications	Journal	5
International Journal of Production Economics	Journal	4
Journal of Cleaner Production	Journal	3
Management Decision	Journal	3
Evaluation and Program Planning	Journal	2
International Journal of Business Excellence	Journal	2
International Journal of Information Management	Journal	2
Journal of Business Economics and Management	Journal	2
Journal of Manufacturing Technology Management	Journal	2
Long Range Planning	Journal	2
Measuring Business Excellence	Journal	2
Sustainability	Journal	2
The TQM Journal	Journal	2
2013 25th Chinese Control and Decision Conference (CCDC)	Conference	1
2012 IEEE International Conference on Fuzzy Systems	Conference	1
ICEB 2007 PROCEEDINGS	Conference	1
IEEE International Conference on Fuzzy Systems (IEEE World Congress on Computational Intelligence)	Conference	1
IEEE software	Conference	1
MATEC Web of Conferences	Conference	1
NAFIPS 2018: Fuzzy Information Processing	Conference	1
Procedia-Social and Behavioral Sciences	Conference	1
Proceedings of the 2011 International Conference on Electrical Engineering and Informatics	Conference	1
Proceedings of the International Conference on e-Business	Conference	1

The Thirteenth International Conference on Electronic Business	Conference	1
Academia Revista Latinoamericana de Administración	Journal	1
Applied Mechanics and Materials	Journal	1
Computers & Industrial Engineering	Journal	1
Computers and Industrial Engineering	Journal	1
Construction Management and Economics	Journal	1
Engineering, Construction and Architectural Management	Journal	1
Global Journal of Flexible Systems Management	Journal	1
Industrial Management & Data Systems	Journal	1
Informatica	Journal	1
Information Systems Management	Journal	1
International Journal for Quality in Health Care	Journal	1
International Journal of Hospitality Management	Journal	1
International Journal of Management Science and Engineering Management	Journal	1
International Journal of Productivity and Quality Management	Journal	1
International Journal of Trade and Global Markets	Journal	1
Journal of Business Strategy	Journal	1
Journal of Modelling in Management	Journal	1
Journal of Statistical Computation and Simulation	Journal	1
Kybernetes	Journal	1
Mathematical Problems in Engineering	Journal	1
Omega	Journal	1
Operations Research Perspectives	Journal	1
Public Money & Management	Journal	1
System Dynamics Review	Journal	1
Tourism Review	Journal	1

Table 1.12: Sources of documents of the sample

Chapter 3

Connecting Strategy and Sustainability

Foreword of Chapter 3

In the literature and in practice, there are various ways to design a sustainable SM, we refer to these 'ways' as *architectures*. In this Chapter, we explore these sustainable architectures and empirically compare them using hard data. This third Chapter thus builds upon and further explores the previous one (see Figure 3.1).

In this study, we conduct the second *design cycle* of our DSR methodology, providing with a more advanced and complex case study of a data-driven SM, which incorporates a significant and current concern: sustainability. This design cycle is based on both the knowledge base from Chapter 1 and on the specific literature on SBSC. The environment of this DSR cycle is composed from skeyes application case, skeyes experts and (potential) SM users.

The term *"sustainable balanced scorecard"*, upon closer examination, may seem misleading. It's essential to clarify that the sustainability aspect lies in how the BSC is applied, rather than implying that the BSC itself is sustainable. A more accurate term would be "Balanced Scorecard *for* sustainability" as it emphasizes the integration of sustainability principles within the BSC framework to strategically manage organizational sustainability. Despite this nuanced distinction, it's worth noting that *SBSC* is a widely adopted term in the literature, and for the sake of consistency and adherence to established conventions, we will retain this terminology throughout the manuscript.

Exploring the importance of the sustainable version of the BSC is crucial for several reasons. Firstly, extensive literature has delved into this concept, making it imperative to assess whether the findings from the preceding Chapter still apply in this context. Secondly, sustainability holds significant relevance in contemporary organizational landscapes, particularly in strategic decision-making. Last, by adapting our framework to incorporate sustainable dimensions, we not only address the immediate concern but also pave the way for broader applications. This adaptability extends beyond sustainability to other perspectives such as IT or digital transformation. Analyzing the BSC through a sustainable lens not only enriches our understanding of this specific version but also opens avenues for similar adaptations in other strategic management contexts.

This Chapter is a co-authored work with Aurélien Clément and Prof. Corentin Burnay and is associated to a finished paper entitled "*Building Green Strategies: An Empirical Comparison of Sustainable Balanced Scorecards Architectures*".

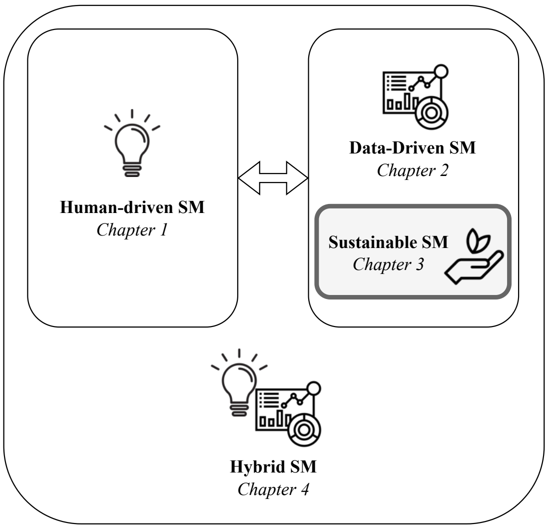

Figure 3.1: Positioning of Chapter 3 in the thesis

3.1 Introduction

Sustainability has risen as a critical issue for a myriad of organizations, especially in the past twenty years, marking a period of surging research activity in this area. The term 'sustainability' itself is a subject of ongoing debate, and lacks a universally accepted definition. In this study, we adopt the definition of sustainability as "*fulfilling current needs without jeopardizing the capability of future generations to satisfy theirs*" as articulated by the World Commission on Environment and Development (WorldCommission, 1987). The notion of '*corporate sustainability*' extends this idea to the organizational level, encapsulating economic, environmental, and social aspects (Ashrafi et al., 2018). Similarly, the term '*corporate social responsibility*' (CSR) underscores the essentiality of incorporating sustainable development, environmental stewardship, social equity, and economic growth into corporate conduct (Wilson, 2003).

A growing number of business leaders are earnestly working to integrate genuine sustainable practices into their organizational operations. A variety of managerial tools and frameworks exist to assist organizations in evaluating their sustainability performance and in the development and implementation of sustainable strategies. These tools frequently employ '*sustainable indicators*' or '*environmental indicators*' (Hammond & Institute, 1995; Székely & Knirsch, 2005), requiring precise definition, measurement, application, and oversight. Existing models, such as the BSC and the SM, offer a foundation that can be adapted to include these indicators comprehensively, an approach now commonly referred to as the SBSC (M. J. Epstein & Wisner, 2001).

Various '*SBSC architectures*' have been proposed to integrate sustainability into BSC, but to date, no empirical study comparing these approaches exists. This lack of comparative analysis is a significant gap with practical implications. It leaves business leaders and practitioners without clear guidance for choosing an effective method tailored to their unique sustainability assessment and management needs, potentially resulting in inefficiency and lost opportunities. Moreover, it fosters inconsistency and ambiguity in sustainability reporting. Such a comparative study could not only inform DM processes but also strengthen the theoretical underpinnings of sustainability management. This brings us to the three research questions of our Chapter:

- "*What are the comparative strengths and challenges associated with the different architectures in the construction of a sustainable Balanced Scorecard?*"
- "*What are the comparative strengths and challenges associated with the different architectures in the use of a sustainable Balanced Scorecard for decision-making purposes?*"

- “*What are the most recommended and discouraged application cases for each type of sustainable Balanced Scorecard architecture?*”

Our study aims to discern the relative strengths and challenges of different SBSC architectures, thereby aiding organizations in selecting an approach that best fits their performance management needs. To address our research question, we create, evaluate, and contrast four different SBSC architectures. Subsequent sections delve into the extant literature on corporate sustainability and its integration into BSC and SM. We then proceed to compare these architectures using empirical data from the Belgian Air Navigation Services Provider, *skeyes*. Our Chapter concludes with a discussion concerning the integration of sustainability elements into the BSC framework.

3.2 Background and related work

Environmental concerns have been escalating over time, and in parallel, scholarly focus on corporate sustainability and its measurement has been intensifying. For example, Mura et al. (2018) identifies ten critical research domains in accounting and sustainable development, providing an overview of the existing body of work. Various studies stress the significance of integrating sustainability into performance management systems. Henri et al. (2016), for instance, points out a robust relationship between a company’s environmental cost monitoring and its actual environmental performance. Similarly, Mura et al. (2018) underscores the importance of aligning sustainability metrics with organizational objectives in DM processes. Contrarily, López et al. (2007) indicates a negative association between performance indicators and CSR, especially in the early stages of implementation.

The conventional BSC is a strategic framework originally composed of four dimensions: Finance, Customers, Internal Business Processes, and Learning & Growth (Kaplan & Norton, 1992). Each of these dimensions incorporates strategic objectives along with associated indicators and metrics. The SM later emerged as an extension of the BSC (Kaplan & Norton, 2000), designed to elucidate the strategy and its required processes and systems, putting a particular emphasis on causal relationships within the framework (Schaltegger & Wagner, 2011). In a seminal work, M. J. Epstein and Wisner (2001) suggested modifying the BSC to include sustainability objectives, giving birth to the SBSC (Bieker et al., 2003).

Research on SBSC is extensive and cuts across various sectors, including aviation (Lu et al., 2018), pharmaceuticals (M. J. Epstein & Wisner, 2001), healthcare (Khalid et al., 2019), higher education (de Andrade et al., 2018), wind energy (Vieira et al., 2017), and public sectors (Mendes et al., 2012), among others. The SBSC also finds application in specific business functions like supply chain management, as demonstrated by Bhattacharya et al. (2014), Qorri et al. (2018), and Reefke and Trocchi (2013). While there is still debate on the net value of SBSC architectures in scientific discourse (see ongoing discussions by Hahn and Figge (2018) and Hansen and Schaltegger (2016, 2018)), the prevailing sentiment leans towards a positive correlation between SBSC and CSR. For example, SBSC aids organizations in embedding environmental and social objectives into their core management systems rather than treating them as additional components (Figge et al., 2002). Moreover, Asiaei and Bontis (2019) posits that the SBSC could serve as a mediator between CSR and overall corporate performance.

While Hahn and Figge (2018) argues that debates over the type of SBSC architecture may be questionable, claiming that SBSCs do not significantly impact corporate sustainability, the scientific discourse around SBSC architectures is robust. Expanding on Hansen and Schaltegger (2016), which reviewed three SBSC architectures (add-on, integrated, and extended) in relation to three types of SBSC hierarchies (strictly hierarchical, semi-hierarchical, and non-hierarchical), this Chapter explores an additional architecture (separated). We focus solely on the strictly hierarchical SBSC, as it aligns most closely with the original BSC framework, where all cause-and-effect relationships ultimately impact financial outcomes. Below is a summary of what we identify as the four primary strictly hierarchical SBSC architectures:

1. ***Add-on architecture***: This approach adds a fifth perspective encompassing social, environmental, and economic aspects to the

traditional four BSC perspectives. Cited by Butler et al. (2011), the original creators of the BSC allow such modifications, making this a straightforward option for organizations. This model is often recommended for companies where sustainability is a strategic focus (M. J. Epstein & Wisner, 2001). Figge et al. (2001, 2002) also advocate for this architecture, especially if sustainability factors aren't easily marketable but are nonetheless strategically relevant.

2. ***Integrated architecture***: This approach incorporates sustainability measures within the existing BSC perspectives (Journeault, 2016). These can be fully integrated into all four perspectives (Figge et al., 2002), or partially integrated, typically into the internal business processes perspective (M. J. Epstein & Wisner, 2001). According to Kalender and Vayvay (2016), this is suitable for companies with an existing BSC wanting to incorporate sustainable measures seamlessly into their strategy.

3. ***Separated architecture***: This design involves constructing a separate SBSC alongside the traditional BSC. This is useful for organizations that either do not have a BSC or prefer not to alter their existing one (Butler et al., 2011; Kalender & Vayvay, 2016). However, this architecture can make it challenging to align the separate SBSC with the organization's core strategy (Kalender & Vayvay, 2016). Figge et al. (2002) suggests that this should only be implemented in conjunction with an integrated SBSC. New perspective names for such a separated SBSC have been suggested by Dias-Sardinha et al. (2002).

4. ***Extended architecture***: This is a hybrid model that both adds a fifth "Society" perspective and incorporates sustainability measures within the traditional four perspectives (Gminder & Bieker, 2002). Essentially, it combines features of the "add-on" and the "integrated" architectures. This approach was initially detailed by Bieker et al. (2001).

We summarize the four approaches to build SBSC in Figure 3.2 based on the number of perspectives of the resulting SBSC (4 or 5 perspectives) and the position of sustainable measures (isolated or blended) towards other measures.

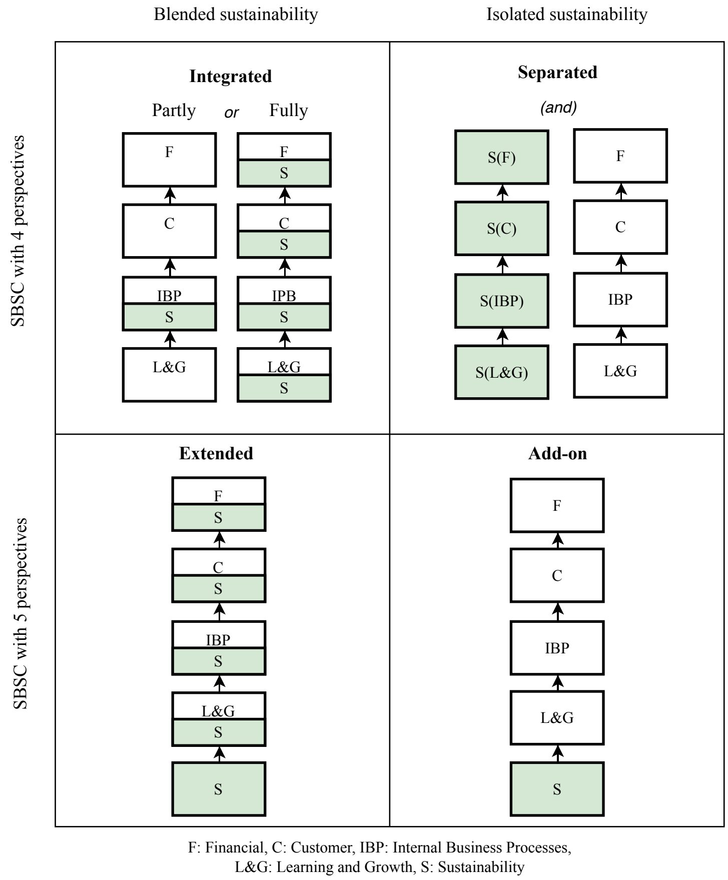

Figure 3.2: The four types of SBSC architectures studied in this Chapter

Prior research has ventured into comparing various SBSC architectures. For example, Jassem et al. (2020) conducted experiments to compare the (partial) integration SBSC with the fifth perspective SBSC, focusing on environmental investment DM. Their findings indicated significant differences between the two architectures, confirming the added complexity of integrating sustainability into the traditional four BSC perspectives – a notion also supported by Hansen and Schaltegger (2016). The study by Jassem et al. (2020) was specific to environmental investment DM and required respondents to make financial decisions aligned with both financial and environmental objectives.

Our research diverges from (Jassem et al., 2020) in several key areas. Firstly, we evaluate four SBSC architectures instead of just two. Secondly, our focus is not on the relationship between architecture and environmental performance outcomes but rather on understanding the pros and cons of each architecture. Unlike Jassem et al. (2020), who mainly conducted a literature review, our conclusions are drawn from a real-world case study and qualitative research. Similarly, Butler et al. (2011) introduces three SBSC architectures and offers a broad discussion of their respective advantages and disadvantages. However, these are general considerations that have not been subjected to empirical investigation. In contrast, our study aims to fill this gap by empirically examining the benefits and challenges of various SBSC architectures.

3.3 Methodology

To address our research question, we carry out two distinct qualitative studies: semi-directive interviews and a large-scale data collection through focus groups (Figure 3.3). This diversity in approaches enhances the robustness of our findings by increasing the reliability of our conclusions. In fact, the use of method triangulation serves as a qualitative research strategy to assess validity by corroborating information from various sources (Patton, 1999).

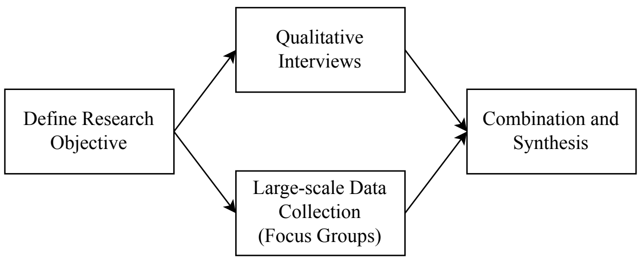

Figure 3.3: Methodological process of this article

The primary objective of this research is to comprehensively examine the strengths and challenges associated with the incorporation of sustainable KPIs within the SM framework. Additionally, it seeks to explore the practical utility of the SM architecture in facilitating data-driven

DM processes based on the type of SBSC architecture. The two studies investigate different aspects to provide a complementary view (Table 3.1), reinforcing the validity of our results.

Study	Methodology	Sample size	SBSC	Number of architectures	Focus
I	Semi-directive interviews	6 people	Data-driven, externally built	Each participant compare the 4 architectures	The use of SBSC
II	Focus group	8 groups (75 people)	Self built	Each group focus on one single architecture	The construction + the use of SBSC

Table 3.1: Focus of the studies

3.4 Study I – Qualitative interviews

3.4.1 Context

Our case study focuses on the Belgian Air Navigation Services Provider (ANSP), *skeyes*, formerly known as *Belgocontrol*. Employing over 930 professionals, skeyes managed approximately 911,000 flights in the year 2022. For this organization, the transition toward sustainability is not merely a trend but a strategic imperative, substantiated by significant investments in various sustainability initiatives. The development of a robust SBSC is increasingly vital for skeyes to effectively navigate its DM landscape. This SBSC will function as a strategic compass, fostering accountability, streamlining resource allocation, enhancing stakeholder engagement, and ultimately providing a competitive edge in an increasingly sustainability-driven global context.

3.4.2 Sample

The sample for the first study is composed of six respondents who belong to different departments at skeyes and desired to stay anonymous (see Table 3.2). Each respondent agreed to have the call recorded which allowed full transcription of the discussion and a more precise comparative analysis. The interviews were concluded at six due to data saturation, as the content discussed by the respondents had become redundant, and no new relevant and truly different information was extracted. They are summarized in a coded double entry table, allowing to clearly identify each architecture's strengths and challenges for every respondent.

ID	Gender	Business area
Respondent 1	Male	Strategy and Performance
Respondent 2	Male	Safety
Respondent 3	Male	Operations
Respondent 4	Male	Environment
Respondent 5	Male	Strategy
Respondent 6	Female	Sustainability

Table 3.2: Descriptive information of the sample

3.4.3 Methodology and data collection

In this first study, we employ a two-step case study methodology, drawing upon the guidelines outlined by R. K. Yin (2009) for case study research. The initial stage involves the creation of the SBSC. Typically, (S)BSCs are constructed through human expertise. However, in the context of this particular case study, this approach is not practical due to the significant time investment required to build a single (S)BSC and the need to develop four (one for each architecture), making manual construction unfeasible. Consequently, we have chosen a more systematic, automated, and cost-effective approach to design these four SBSC. This involves the adaptation of a data-driven framework based on Pirnay and Burnay (2022), using performance data sourced from the Belgian Air Navigation Services Provider, *skeyes*. In the second step, the four SBSC are exposed to business users for feedback. We evaluate and compare these SBSC architectures through qualitative, semi-directed interviews.

Building data-driven SBSC

Our empirical analysis will make use of an updated version of the developed and validated data-driven methodological framework (Pirnay &

Burnay, 2022). This framework addresses the shortcomings associated with relying solely on human expertise for constructing BSC, particularly concerning accuracy, completeness and longitudinal perspective. We posit that this methodological framework has the potential to facilitate the creation of our four SBSC that are not only more accurate but also more rapidly developed, cost-effective, and robust. In fact, Pirnay and Burnay (2022) have addressed these challenges by proposing a methodological framework that harnesses operational data and employs data mining techniques to systematize the identification of causal relationships within the SMs of the BSC. Their approach involves the application of time series methodologies and Granger causality tests, ultimately enhancing the efficiency of this strategic tool. The methodological framework, adapted to our study, is illustrated in Figure 3.4 and depicts the three major steps we undertake:

- **Phase I: Set-up**: aims to introduce the scope of the project and serves as the foundations of the whole process. As shown in the diagram, this is the phase where the selection of the KPIs occurs through discussions with the organization's experts. In our particular case, we discussed the KPI selection and classification with skeyes' Performance Director to ensure the data was representative of the core business. To achieve this, we measure the Pearson correlation coefficient to ascertain that the KPIs are not correlated with each other, thereby ensuring that they provide genuine and distinct information. We also use this phase to assess whether the KPI is eligible for the data-driven analysis, according to Pirnay and Burnay (2022), regarding data availability and quality. The data should have been collected accurately, without any missing values. It must also be up-to-date to accurately represent the current state of the organization. Furthermore, it is preferable to have data that spans a substantial time frame and has the highest level of granularity possible. Among the selected indicators, we have defined which one are sustainable KPIs.
- **Phase II: Data-driven**: aims to produce a SBSC relying solely on quantitative statistical analyses. Once the data has been trans-

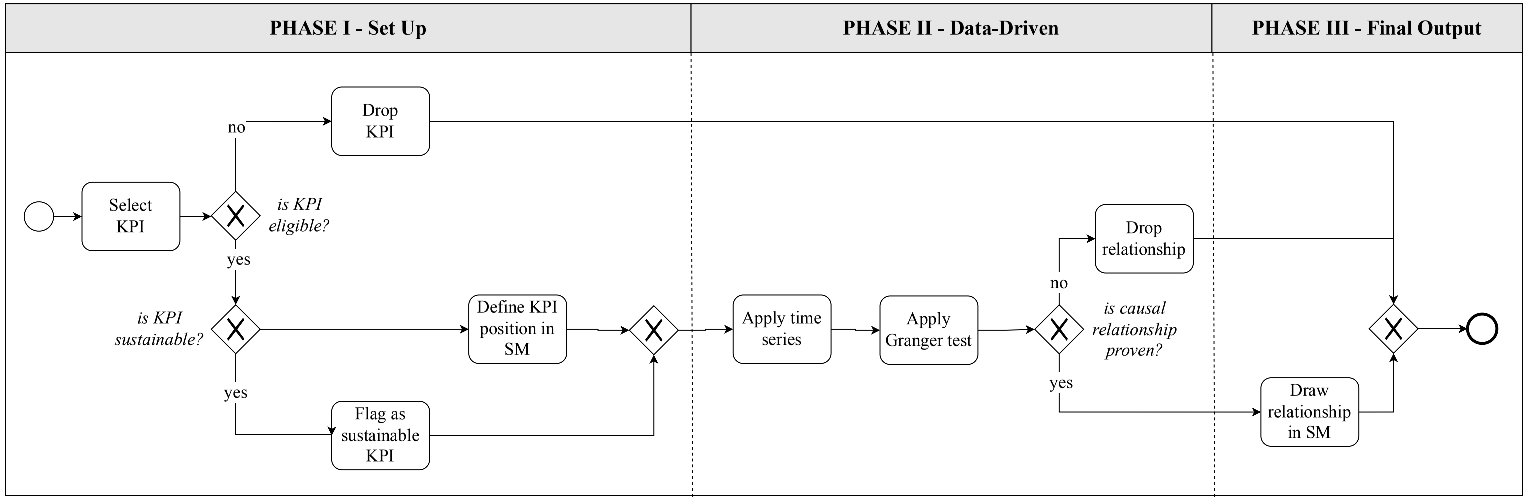

Figure 3.4: Data-driven framework to build SBSC

formed into time series, we determine existing causal relationships between the KPIs through a Granger hypothesis test (Granger, 1969). Granger tests can be regarded as an advanced iteration of correlation analyses for multivariate time series data. They extend beyond mere correlation by enabling the detection of causal effects, as opposed to mere correlation effects. This is achieved by identifying both the cause indicator and the effect indicator within the data. These tests, usually used in financial analysis and transposed to the present field, help verify when a temporal series A better explains the variation of another series B than B's own history. In the interpretation of Granger tests, we adhere to the common significance level of 5%, i.e. the percentage risk of error.

- **Phase III: Final output**: using the outputs from the previous phase, we then build four different SBSC architectures. Causal relationships are graphically represented by arrows originating from the cause KPI and directed towards the effect KPI. The designs are kept as simple as possible so that the only differentiating factor is the architecture itself, and all share the same minimalist color scheme – where only sustainable indicators as well as their connections are represented in green. To avoid overloading the graphs, which could disrupt the comparison of the different architectures, only the KPIs with connections identified by the Granger tests were kept.

Evaluation and comparison of the SBSC architectures

In order to compare the four SBSC, we carry out a qualitative research through semi-structured interviews with skeyes' experts, adhering to best practices as discussed by Rubin and Rubin (2011) and Kvale and Brinkmann (2009). The interview guide includes open-ended questions and a more projective approach that will help to determine each architecture's strengths and challenges. The respondents were recruited through an introductory emails presenting the outline of the research. All interviews took place online in July and August 2023.

3.4.4 Results from study I

Building the data-driven SBSC

The SBSCs resulting from the data analysis and corresponding to the four architectures to be compared are presented in the following pages.

Phase I : Set-up. In this case study, we have employed a set of 20 KPIs to construct the four SBSC through a data-driven analysis. The process of selecting these KPIs and categorizing them as sustainable or not was a result of extensive discussions with skeyes' business experts. It is unanimously agreed that these KPIs represent effectively the majority of their business strategy. These KPIs can be categorized into three variations: ER ("en-route", representing flights controlled in the sky without takeoff or landing in the territory), Global (encompassing "en-route" and five airports in Belgium), and EBBR (specific to Brussels Airport). Further details and definitions of each KPI and its variations are provided below in Table 3.3.

We collected data in a specific two-year time frame, spanning from 2018 to 2019. This choice stems from the significant disruptions the aviation sector experienced during 2020 and 2021 due to the Covid-19 pandemic and associated lockdowns, making these years non-representative of normal operating conditions for the organization. We choose to work on a monthly granularity basis as this was not possible to obtain some KPI data at a daily basis and we rigorously ensure that there are no missing values in our dataset. The correlation analysis highlighted three points of attention where KPI's variations were too correlated, which can deter the validity of the results and arbitrary choices to keep the global variation have been made.

Phase II: Data-driven. Upon transforming our data into time series format, we are able to carry out the Granger hypothesis tests to validate the presence or absence of causal relationships among skeyes KPIs. The results of these hypothesis tests are presented in Table 3.4.

Phase III : Final output. Based on the results of the Granger tests and the selection of architectures presented in Section 3.2, we proceed to create four SBSC for skeyes. The add-on SBSC architecture is presented in Figure 3.5, the integrated SBSC architecture is presented

KPI name	**KPI short definition**	**BSC perspective**	**Sustainable KPI**	**KPI variation**	**Data finest granularity**
Service Units en-route	Number of BE-LUX en-route service units	Finance	no	ER	Monthly
Service Units terminal	Number of terminal service units at Belgian airports	Finance	no	Global, EBBR	Monthly
CDO Noise	Rate of Continuous Descent Operations flown (reduced thrust and noise, environmental benefits)	Customer	yes	Global, EBBR	Daily
CDO Fuel	Rate of Continuous Descent Operations flown (reduced thrust and noise, environmental benefits)	Customer	yes	Global, EBBR	Daily
En-route flights delayed	Rate of en-route flights being delayed by skeyes (ATFM delay)	Customer	no	Global	Daily
Arrival flights delayed	Rate of arrival flights being delayed by skeyes (ATFM delay)	Customer	no	Global	Daily
Safety operational occurrences (Freq)	Rate of safety operational occurrences (all severities)	Customer	no	Global, EBBR	Daily
Flight Hours Controlled	Sum of the flight hours controlled by skeyes units (ACC, APP, TWR)	Customer	no	Global, EBBR	Daily
Movements Airports	Number of airport movements controlled by skeyes	Customer	no	Global, EBBR	Daily
Movements CANAC	Number of en-route movements controlled by CANAC	Customer	no	ER, EBBR	Daily
Variable Taxi Time	Percentage of aircraft having a taxi time no-longer than their prescribed default taxi time	Customer	yes	EBBR	Monthly
Arrival Sequencing and Metering (ASMA) additional time	Difference between the actual ASMA time and a statistically determined unimpeded ASMA time based on ASMA times in periods of low traffic demand	Customer	yes	Global, EBBR	Monthly
Horizontal en-route flight efficiency	Measure the difference between great-circle distance and actual flown distances in KEP or KEA. KEP is based on flight plan, KEA is based on actual radar data	Customer	yes	Global	Monthly
En-route delay per flight	En-route ATFM delay per movement	Internal Business Process	no	Global	Daily
Arrival delay per flight	Arrival ATFM delay per movement	Internal Business Process	no	Global, EBBR	Daily
Missed Approaches	Number of missed approaches at airports	Internal Business Process	no	Global, EBBR	Daily
Traffic complexity skeyes	Representation of the density of traffic and intensity of potential interactions between traffic	Internal Business Process	no	Global	Daily
Availability of critical systems	Percentage of availability of critical systems supporting ATC operations	Learning & Growth	no	Global	Daily
Availability of very critical systems	Percentage of availability of very critical systems supporting ATC operations	Learning & Growth	no	Global	Daily
ATCO Hours on Duty	Number of hours “ATCOs in OPS” spent on duty in OPS, including breaks and overtime in OPS	Learning & Growth	no	Global	Monthly

Table 3.3: Sample of 20 KPIs to build the SBSC’s

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38
1. SERVICE UNIT ER																																						
2. SERVICE UNIT TERMINAL Global																		✓													✓							
3. SERVICE UNIT TERMINAL EBBR																						✓									✓							
4. CDO NOISE Global						✓																																
5. CDO NOISE EBBR																																						
6. CDO FUEL Global	✓													✓				✓															✓					
7. CDO FUEL EBBR											✓							✓								✓		✓					✓					
8. ER FLIGHTS DELAYED (skeyes)																																		✓				
9. ER FLIGHTS DELAYED (Europe)			✓											✓		✓																						
10. ARR FLIGHTS DELAYED (skeyes) Global													✓		✓			✓																				
11. ARR FLIGHTS DELAYED (Europe) Global	✓																																					✓
12. SAFETY OP OCC Global			✓																																			
13. SAFETY OP OCC EBBR																												✓										
14. FLIGHT HOURS CONTROLLED Global																																	✓					
15. FLIGHT HOURS CONTROLLED EBBR																		✓																				
16. MVMT PRU Global		✓																													✓							
17. MVMT PRU EBBR		✓																													✓							
18. MVMT CANAC (OVERFLIGHTS) ER													✓										✓															
19. MVMT CANAC (BXL APPROACH) EBBR																															✓							
20. ER DELAY PER FLIGHT (skeyes)	✓	✓	✓							✓						✓		✓	✓					✓							✓			✓				
21. ER DELAY PER FLIGHT (skeyes CRSTMP)																									✓						✓			✓				
22. ER DELAY PER FLIGHT (Europe)		✓												✓		✓																						
23. ER DELAY PER FLIGHT (Europe CRSTMP)																					✓				✓													
24. ARR DELAY PER FLIGHT (skeyes) Global													✓	✓											✓													
25. ARR DELAY PER FLIGHT (skeyes CRSTMP) EBBR																							✓							✓	✓							
26. ARRIVAL DELAY PER FLIGHT (Europe) Global								✓												✓	✓								✓					✓				
27. MISSED APPROACHES Global	✓	✓	✓												✓	✓	✓		✓												✓			✓				✓
28. MISSED APPROACHES EBBR			✓													✓			✓																			
29. TRAFFIC COMPLEXITY SKEYES Global	✓								✓													✓																
30. AV OF CRITICAL SYSTEMS Global																									✓				✓						✓			
31. AV OF V CRITICAL SYSTEMS Global																								✓	✓					✓								
32. ATCO HOURS ON DUTY Global		✓	✓													✓	✓			✓																		
33. ATCO HOURS ON DUTY ER		✓		✓	✓															✓																✓	✓	
34. ATCO HOURS ON DUTY EBBR				✓																										✓	✓							
35. VARIABLE TAXI TIME EBBR														✓			✓											✓										
36. ASMA ADDITIONAL TIME Global																																						
37. ASMA ADDITIONAL TIME EBBR		✓														✓								✓														
38. HORIZONTAL FLIGHT EFFICIENCY Global									✓													✓																

Table 3.4: Granger test results (sig. level of 5%)

in Figure 3.6, the separated SBSC architecture is presented in Figure 3.7 and the extended SBSC architecture is presented in Figure 3.8.

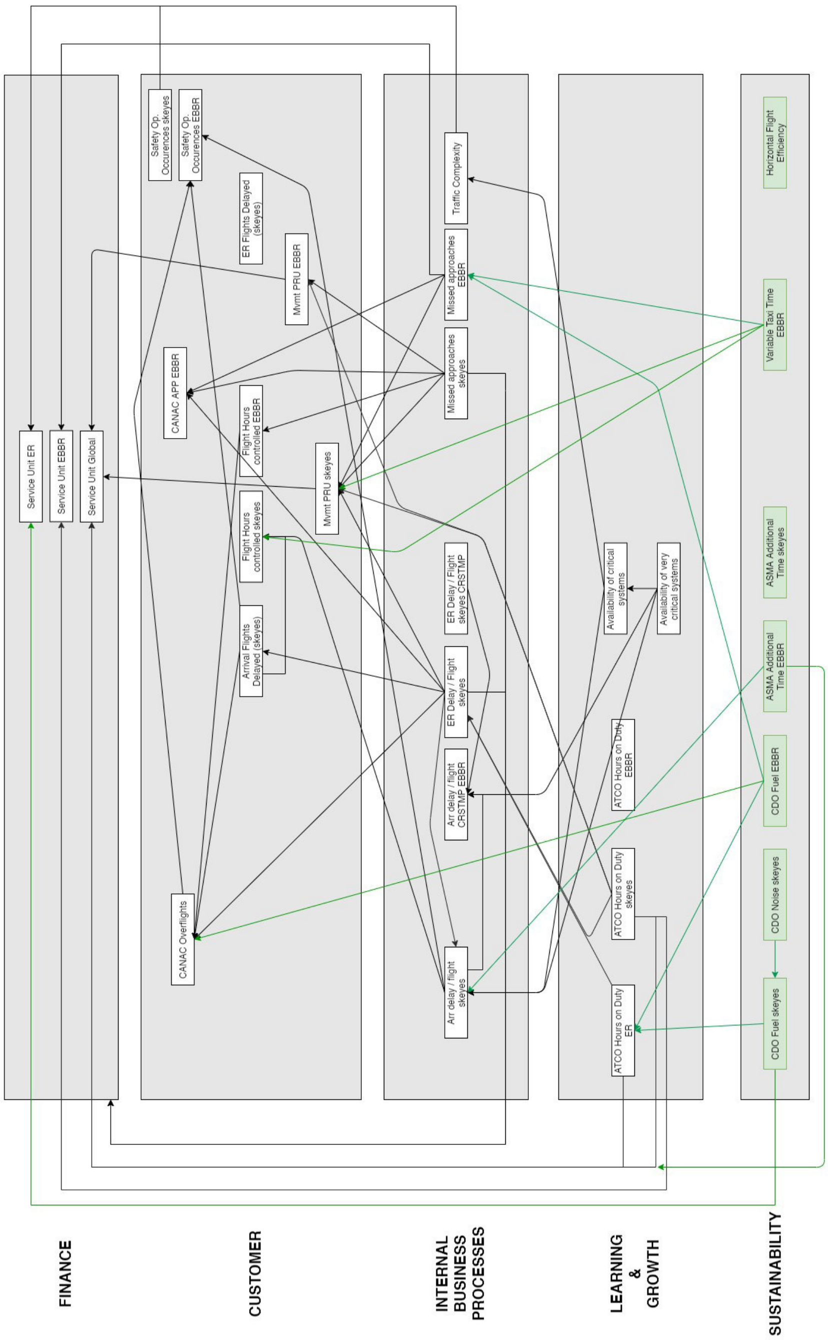

Figure 3.5: Add-on data-driven SBSC for skeyes

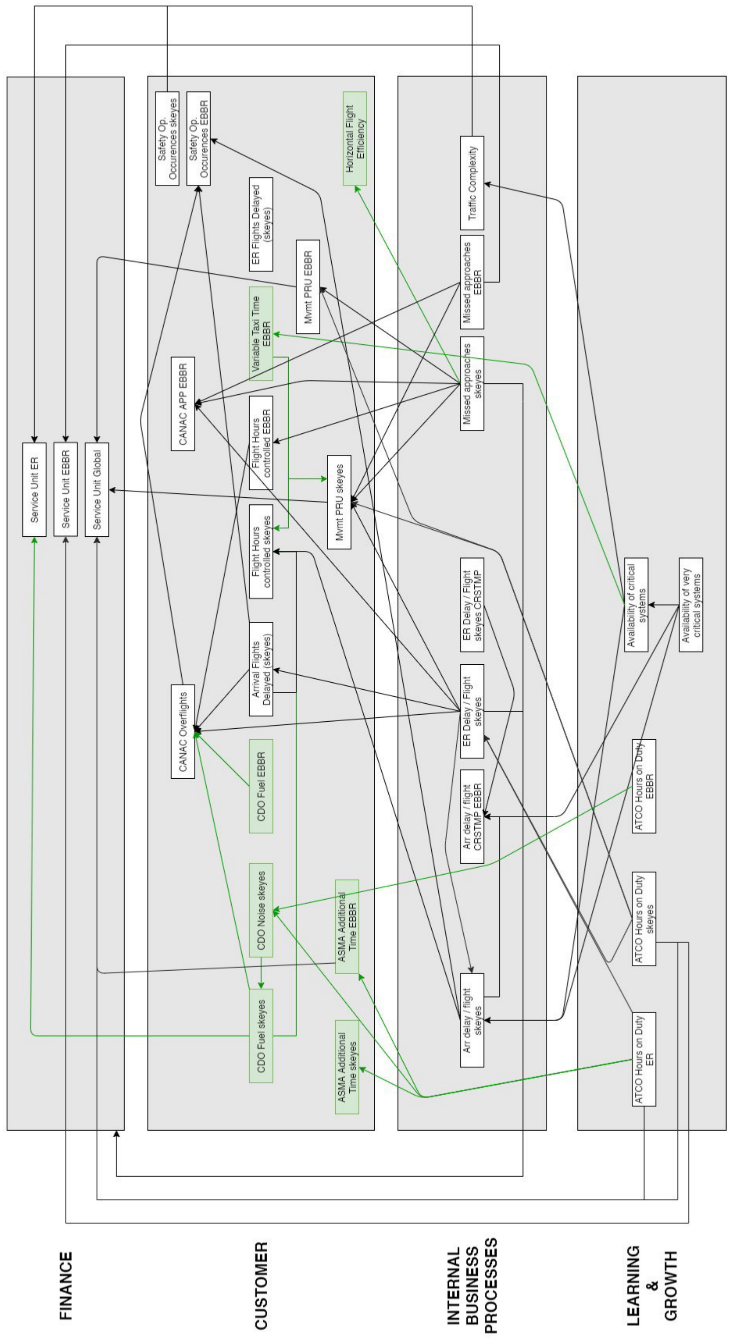

Figure 3.6: Integrated data-driven SBSC for skeyes

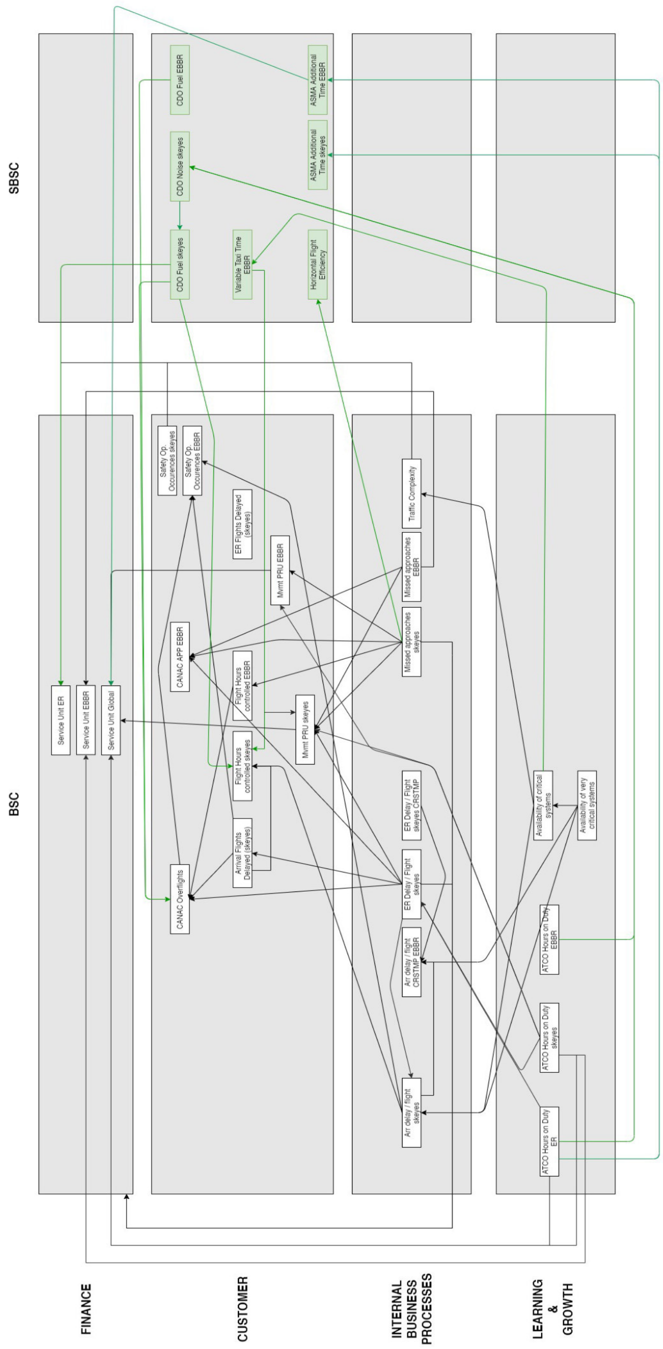

Figure 3.7: Separated data-driven SBSC for skeyes

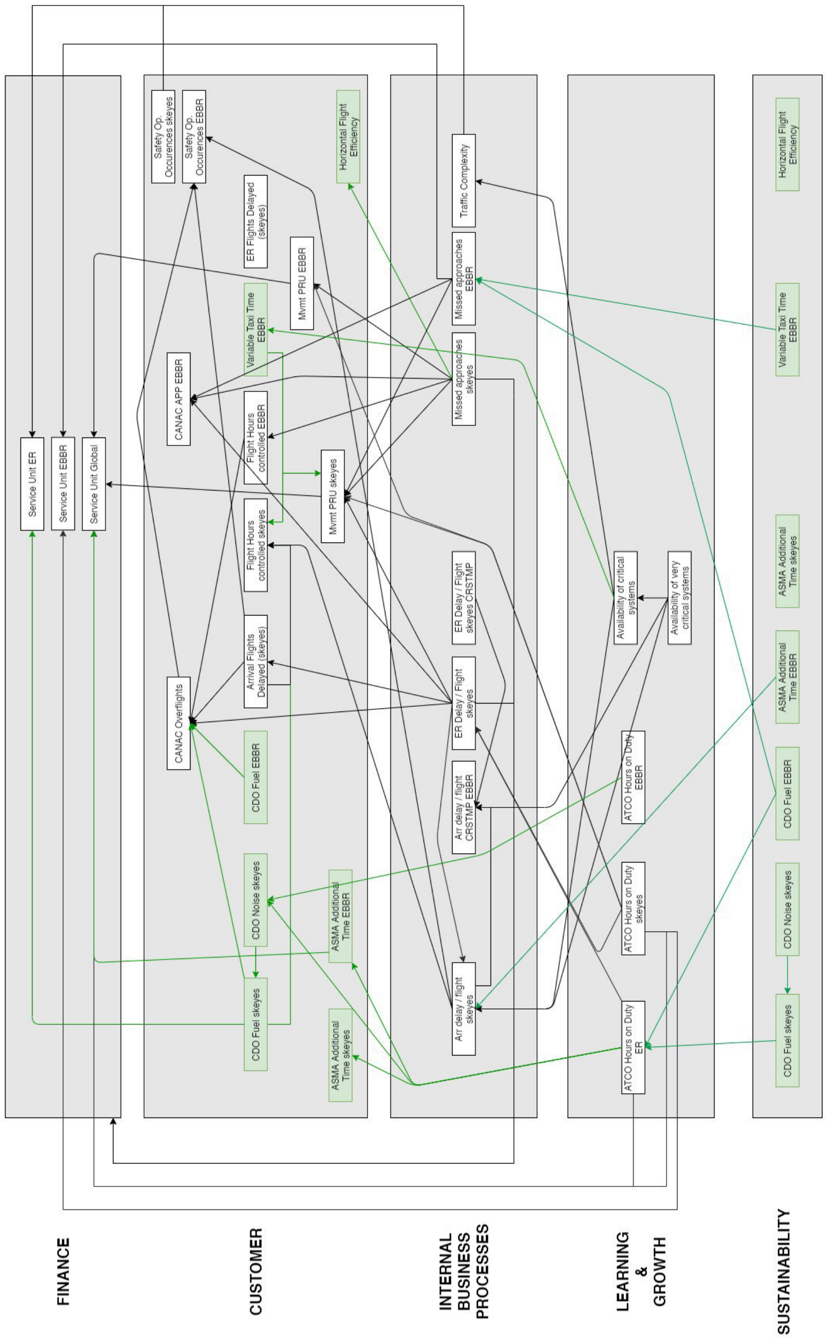

Figure 3.8: Extended data-driven SBSC for skeyes

Comparing the 4 SBSC architectures

Following the interviews analyses, we discuss strengths and challenges that stand out for each architecture.

Firstly, the **Add-on Architecture** introduces a fifth dimension to the traditional BSC perspectives. This architecture received a tepid reception from respondents in comparison to the other three models examined. It is noteworthy to emphasize that this architecture was not explicitly designated as the least preferred option. Respondent 1 characterized the Add-on Architecture as "intricate" while also acknowledging its "comprehensive" nature. Unfortunately, the visual complexity arising from the number and extent of arrows utilized in its schematic representation adversely affected its perceived utility for *skeyes*.

> *"The visual diagram of this architecture suffers from a lack of clarity and aesthetic appeal, largely due to the excessive length and number of arrows. Such elements obstruct efficient comprehension and thus, its practical application."* – Respondent 2.

The **Integrated Architecture** garnered a generally favorable response from respondents, albeit with some reservations. A key positive aspect noted was its integration of sustainability metrics alongside skeyes' strategic indicators, thereby emphasizing the role of sustainability as integral to the organization's core business objectives. However, this architecture was also perceived as being "hard to digest" (Respondent 2) and "less favorable than the Separated architecture" (Respondent 1). Further commentary on this particular architecture was relatively limited.

In contrast, the **Separated Architecture** elicited polarized opinions among the respondents, highlighting its distinctive strengths and challenges. One notable advantage of this architecture is its ability to accentuate the prominence of sustainability within the organization's strategic objectives.

> *"In the context where the primary objective is to delineate the relationship between sustainability and other business in-*

> *dicators, this architecture provides a more distinct visual guide. It facilitates the tracking of how sustainability initiatives correlate with existing indicators, which might otherwise be subsumed within the four traditional layers."* – Respondent 2.

This divergence in opinion underscores the context-dependent utility of the Separated architecture, suggesting that its appropriateness may vary based on specific organizational goals and stakeholder preferences.

Another benefit of the **Separated Architecture** is its capability to articulate connections between sustainable KPIs and the core business objectives, thereby offering a clearer framework for interaction between the two. As noted by Respondent 4, "It provides a more lucid understanding of how the conventional business aspects interact with sustainability."

In terms of design practicality, this architecture is viewed as "easier to implement" (Respondent 1) and possesses adaptability for future modifications:

> *"I appreciate the conceptualization of sustainability as a foundational pillar that interconnects with every facet of the organization's operations. This architecture allows for the seamless incorporation of other elements like Corporate Social Responsibility, thus making it more versatile."* – Respondent 3.

According to the respondents, the separated architecture also scores high on ease of explanation and intuitive design. Respondent 1 described it as "easier to explain," while Respondent 3 found it to be "more intuitive." Additionally, the architecture is seen as less cluttered, which aids in its interpretability:

> *"Incorporating an increasing number of indicators complicates the visual representation. However, this challenge is somewhat mitigated in the separated architecture as new elements can be conveniently placed to the right, making it more manageable."* – Respondent 2.

The last merit pointed out by Respondent 1 pertains to the architecture's utility for DM:

> *"Certainly, the separated architecture offers the most lucid platform for informed decision-making, and also yields a visually coherent presentation suitable for executive-level interpretation. What is crucial here is not just the logical interconnections among various metrics, but also the architecture's capacity to be clearly understood and presented at higher organizational levels."* – Respondent 1.

This array of advantages indicates that the Separated Architecture not only clarifies the relationship between sustainability and core business strategies but also offers greater flexibility, ease of interpretation, and utility for DM.

On the other hand, the separated SBSC architecture also receives some negative feedback from the qualitative interviews. Unlike the first advantage mentioned earlier for this architecture, some respondents regret the separation of the two BSCs. Indeed, it gives them the impression that sustainability is something standalone, which should be addressed separately:

> *"[It] gives the impression like it's something to be treated separately. I know it's not the idea, but you give this kind of impression that it's standalone compared to when it's actually integrated."*
> – Respondent 4.

> *"The separated architecture is my second least favorite because I feel like there sustainability, seems very separated, somehow."*
> – Respondent 6.

Another drawback reported for this architecture is the sense of lacking a cause-and-effect connection, thus falling short of the primary benefit of the BSC tool:

"I think perhaps, only visually, you could be tricked into thinking that these [sustainable KPIs] exist within a vacuum and that, you know, other considerations are unaffected or affected to a lesser extent. [...] I'm looking at it now, it suggests that these [sustainable KPIs] can exist autonomously. Perhaps it doesn't show exactly the kind of relationship that I've just described where one change implies a cause-and-effect in something else. "
– Respondent 5.

Lastly, the **Extended Architecture** elicited divergent opinions among the respondents. One central point of contention was the repetitive inclusion of sustainability indicators both within their specialized perspective (the fifth pillar) and across the traditional BSC perspectives. For some respondents, this redundancy created a level of confusion:

"The Extended Architecture is less intuitively understood and introduces unnecessary complexity through indicator duplication. Although I understand the initial rationale behind this repetition, it diminishes the architecture's appeal for me. I would be inclined to dismiss this option." – Respondent 1.

"The visual clutter caused by repeating sustainability indicators at multiple places in the architecture complicates its interpretation. Complete integration seems counter-intuitively difficult to articulate and may necessitate a preparatory tutorial to be comprehensible." – Respondent 2.

Contrastingly, some respondents appreciated the redundant placement of KPIs, arguing that it facilitated a more nuanced and thorough understanding of the organization's performance. They pointed out that the architecture's complexity allowed for the identification of feedback loops, which were not readily visible in other models:

"Despite its complexity, the Extended Architecture excels in highlighting interdependencies between various performance

> *indicators. It provides a more holistic perspective by illuminating how one area can impact another, thereby adding value to the strategic evaluation."* – Respondent 4.

> *"The Extended Architecture is my preferred choice as it seamlessly integrates sustainability into the overall business strategy. It effectively demonstrates that sustainability is not a peripheral concern but a central component of the organization's operations."* – Respondent 6.

In summary, the Extended Architecture polarized opinions due to its complex design featuring redundant KPIs. While some respondents found it difficult to interpret, others appreciated its capacity to provide a more comprehensive understanding of strategic interdependencies.

3.5 Study II – Focus groups

3.5.1 Context

In order to build upon the findings of the first study, a second study was undertaken with a double objective. First, it aimed to reinforce and validate the outcomes of the first study by replicating the results in a new context. Second, the focus of this second study is also to explore new elements not addressed with the semi-directive interviews. While the first study concentrated solely on the utilization of strategic tools, the second study extended its scope to examine the process of constructing a SBSC from scratch. The initial study had provided participants with pre-existing SBSC, whereas in this follow-up study, participants were actively involved in both building and using these tools. This shift in methodology allowed for a more comprehensive understanding of the strategic DM process.

3.5.2 Sample

The research was conducted on October 2023, and involved a total of 76 participants. These participants represented a diverse heterogeneous sample of individuals with a keen interest in sustainable strategic management. Among them, 62 participants are professionals with technical profiles such as infrastructure manager, data analyst, business analyst, developer, cloud expert, among others. The remaining 14 participants are master's students specializing in analytics and digital business. To facilitate a collaborative learning environment, the participants were organized into 8 mixed groups, fostering a blend of master students and industry experts (Table 3.5).

Participants	**Focus Group 1**	**Focus Group 2**	**Focus Group 3**	**Focus Group 4**	**Focus Group 5**	**Focus Group 6**	**Focus Group 7**	**Focus Group 8**	***Total***
Cyber security	1	2	2	1	1	1	1	2	*11*
Cloud expert	2	1	2	2	1	2	1	1	*12*
Business Analyst	1	2	1	1	1	1	2	1	*10*
DotNet Developer	2	2	1	1	2	2	1	2	*13*
Data Analyst	1	1	1	1	1	1	1	1	*8*
Java Developer	2	1	1	1	1	1	2	1	*8*
Master's students	2	1	2	2	2	2	1	2	*14*
Total	*9*	*10*	*10*	*9*	*9*	*10*	*9*	*10*	*76*

Table 3.5: Composition of the eight focus groups

3.5.3 Methodology and data collection

For this second study, we apply a focus group methodology (Rabiee, 2004). Focus groups are group interviews in which a moderator guides the interview while a small group of around eight people discusses a certain topics (Morgan et al., 1998). In this case, the topic of the focus groups is the construction and use of a (predetermined) SBSC architecture. We carried out a total of eight focus groups, which ensured that each of the four SBSC architecture is examined by at least 2 groups. The focus groups took place during a one-day workshop on the theme of '*sustainable IT*', organized by both a University Research Center in digital transformation and an ICT Competence Center. Before engaging in the focus groups, all participants received an oral introduction to sustainable strategic management and the SBSC/Sustainable SM, ensuring that they had a foundational understanding of the subject. The participants were then separated into eight groups and the research activity itself had a total duration of 2 hours, providing sufficient time for the participants to delve into discussions, share insights, and collaborate on the research objectives. The collection of information was made possible thanks to the eight-steps protocol described hereafter:

- **Step 1: Brainstorming on Sustainable organizational KPIs.** The group starts with a brainstorming session to generate some ideas on sustainable KPIs. This serves as a contextualized warm-up exercise. They note down all the KPIs that come to their mind;
- **Step 2: Placing the Retrieved Sustainable KPIs in the Designated SBSC Architecture.** They create a preliminary visual representation of their SBSC architecture. They identify where each KPI could integrate the tool in more detail and discuss freely about it;
- **Step 3: Linking All KPIs in the SBSC Architecture.** They establish causal relationships between their newly added sustainable KPIs and the generic KPIs already present in the SBSC architecture. Once more, the group discusses freely about it;
- **Step 4: Analysis of the strengths and challenges Encountered during KPIs Placement and Linking).** The moderator ask the group to identify in more detail the ease and difficulties they encountered while constructing the SBSC in steps 2 and 3 and to synthesise it into a mind map;
- **Step 5: Using SM for DM Role-plays.** The focus group go deeper into how SM can be used by answering DM questions and scenarios, based on their own constructed SBSC. While doing so, the discuss out loud;
- **Step 6: Analysis of strengths and challenges Encountered during SM Utilization.** The moderator ask the group to examine in more detail the strengths and challenges associated with using SM for DM, especially focusing on the use of sustainable KPIs and sustainable perspectives, and to synthesise it into a mind map;

- **Step 7: Synthesize Conclusions into a Mind Map.** They review and complete a detailed Mind Map summarizing their findings, highlighting KPIs, their integration into the SBSC architecture, strengths, challenges, and the use of SM for DM;
- **Step 8: Review and Discussion.** They take the time to review their work and briefly discuss it with other participants to gather additional feedback.

In order to analyze the results of the focus groups, we employ both the note-based analysis and the memory-based analysis (Morgan et al., 1998). The note-based analysis is based on both the personal notes of the researcher present during the focus group but also based on the notes of the participants, taken during the activity. Indeed, the participants were asked, complementary to making a synthesis of their discussion, to write down all the questioning and difficulties they have encountered during the research activity. The memory-based analysis is based on the discussion between the groups and the researchers which have not been written down for ensuring a good discussion flow. All the results were later encoded by the researcher in a double entry table, similar to Table 3.6 for an effective comparison.

3.5.4 Results from study II

Following the eight focus groups, we discuss strengths and challenges that stand out for each architecture.

Firstly, the **Add-on Architecture** was analyzed by focus groups 1 & 8. Group 8 brainstormed about 14 sustainable KPIs but could only place 5 in their SBSC architecture. Indeed, as the add-on architecture only allows for placing sustainable KPIs within a single perspective, just below the SBSC. Therefore, it is evident that a choice must be made in order not to overload the tool; a first prioritization arbitration of the KPIs is thus necessary. However, and equally supported by focus group 1, the construction of the map was quite easy. Indeed, as the first construction step is to place sustainable KPIs in the different perspectives. Here, as they didn't have a choice (only one perspective), this was done very quickly. However, both focus groups have discussed a lot during for linking the sustainable KPIs in the SBSC. As the sustainable perspective is at the basis of the tool, they could connect their sustainable KPIs with any of the other KPIs for the SBSC. They had to take some time to analyze all possibilities and discuss each of them. This characteristic also impeded the usability of the SBSC, creating a lot of arrows in the visual tool. Finally, although the sustainable perspective is put at the basis of the tool, where all connections start to attain the financial perspective in the end, the sustainable perspective has been seen as treated quite separately from the rest of the strategy. Thus, both focus groups would not recommend this SBSC architecture for organizations focusing on sustainability.

The **Integrated Architecture** was analyzed by focus groups 3 & 4. Group 3 was able to retrieve 22 sustainable KPIs and were able to place them all on the integrated SBSC architecture. Indeed, as the architecture offers a place for sustainability at each level, there is no trivial choice to make on which KPI to include or not in the SBSC. However, it was stated by both focus groups during the construction of the SBSC that it was difficult to choose the correct perspective to put the sustainable KPIs in. By looking at the resulting SBSC, we can visually see that fewer sustainable KPIs are present in the financial and the customer perspectives than on the two other ones. In the utilization of their SBSC architecture, they noted that it was very well structured and that it is suitable for organization focusing on sustainability as it is present in every aspect of the strategy.

The **Separated Architecture** was analyzed by focus groups 2 & 5. Both groups were able to list about twenty sustainable KPIs and place nearly all of them in their separated SBSC architecture. Similarly to what was discussed in the integrated architecture's focus groups, the fact that there is a sustainable decline in each perspective did not impose any restrictions on the number of KPIs to be kept and placed in the SBSC. The structure was very easy to understand and the separated architecture was then easy to build. However, this architecture raised more discussions in the utilization part of the focus group exercise. Indeed, as the SBSC is separated from the classical BSC, the DM scenarios were difficult to apply. For instance, the sustainability being separated, it was not necessary to look at it to answer non sustainable strategic questions. The lack of connection with the classic version of the BSC does not help for integrating sustainability in DM. For these reasons, the two focus groups highly discourage having this type of SBSC architecture in organizations focused on sustainability or those that wish to position themselves regarding sustainability. However, the ease to construct the SBSC is seen as a serious advantages, for small companies for instance.

Lastly, the **Extended Architecture** was analyzed by focus groups 6 & 7. This more complex SBSC architecture was highly discussed during the focus groups. Group 6 was very confused during the construction of the SBSC. Indeed, the group had a hard time to decide whether to allocate the sustainable KPIs in the sustainable perspective below, in the above perspectives, or in both (with duplication). They also expressed difficulties in finding sustainable KPIs for some perspectives, particularly for customers and finance. The same conclusion applies for focus group 7 which did not integrate any sustainable KPIs in these two perspectives. Moreover, with 5 perspectives and sustainability at every lever, the number of causal links between the KPIs exploded. During the utilization of the extended architecture for DM scenarios, both groups affirmed that it was hard to navigate the map to make decisions, that the SBSC looks very messy and lacks precision. Based on these observations, they recommend this extended architectures for small and young organization with less KPIs. However, on a positive note, this extended architecture gave the feeling to group 6 that the sustainability issue was very well taken into account for the organization. Thus, they encourage sustainability-focused organizations to opt for this choice of SBSC.

3.6 Discussion

3.6.1 Synthesis of the comparison of SBSC

Table 3.6 presents a summary of the characteristics of each architecture, derived from both interviews and the focus groups analyses. Additionally, we offer recommendations regarding suitable use cases and those to be avoided for each architecture. Overall, these findings may help practitioners and researchers select the relevant architecture based on contextual and organizational factors.

Architecture	Construction	Utilization	Use Cases
Add-on	***Strengths*** Quick to adapt from classical BSC by integrating the sustainable KPIs in a single perspective.	***Strengths*** Comprehensive; provides a global vision; easy to share with other people.	***Recommended*** Organizations seeking a comprehensive overview of the strategic relationships; Scenarios requiring a specialized 'Sustainable' (or similar name) perspective depending on its activities; Sustainability is not the core business but organization put a little emphasis on sustainability.
	Challenges Connect the sustainable KPIs to all above perspectives creates a numerous amount of arrows; select a subset of sustainable KPIs to avoid overloading the sustainable perspective and overall SBSC.	***Challenges*** Intricate and visually complex; hard readability because of the number of arrows; lack of clarity; sustainability is left aside.	***Discouraged*** Not suitable for organizations focusing a lot on sustainability; cases where quick interpretation is needed; visual clarity is a priority for the organization.
Integrated	***Strengths***	***Strengths***	***Recommended***

	Very structured; same structure as classical BSC.	Aligns sustainability with core business; More sustainable oriented.	Established organizations committed to sustainability; when sustainability and business goals closely align.
	Challenges Dispatching sustainable KPIs in the classical perspective, especially in Financial and Customer; require a large amount of KPIs to place in each perspective.	***Challenges*** Hard to digest; cause-and-effects connections are not evident.	***Discouraged*** Organizations without sustainability as core strategic objective; Not for fast DM contexts; Not for small/young organizations due to complex settings.
Separated	***Strengths*** Easy structure to understand as it is the same as the classical BSC; Easy to integrate the sustainable KPIs in the because it is separated.	***Strengths*** Clearer visual framework to use; clear cause-and-effects in each SBSC.	***Recommended*** Organizations in the nascent stages of incorporating sustainability; flexibility is a priority; a BSC already exist in the organization.
	Challenges	***Challenges***	***Discouraged***

	Requires a large amount of KPIs to place in each sustainable perspective.	Sustainability is separated thus it's not necessary to look at the SBSC for "non sustainable" strategic questions; No link with classical (non sustainable) KPIs of the organization, it does not help for sustainable DM; Perceived as separating sustainability and strategy; Lacks cause-and-effect connections.	Not suitable for organizations focused on sustainability, that wishes to position themselves regarding sustainability; when sustainability is not a core strategy of an organization; small organizations with few KPIs; need of an integrated and comprehensive view.
Extended	***Strengths*** *(no comparative advantages)*	***Strengths*** Offers the mot comprehensive overview of the strategy of an organization and the link with sustainability; the redundancy on some KPIs make possible to interpret the interdependency links as feedback loops.	***Recommended*** Strong focus on sustainability; sustainability is the core business; complex organizations with multiple interacting objectives; high-stakes DM environments.
	Challenges	***Challenges***	***Discouraged***

	Dispatching sustainable KPIs in the correct perspective; allocating sustainable KPIs is made very difficult by the duplication of the sustainable perspective; need to arbitrary duplicate or delete some sustainable KPIs; apparent difficulty to find sustainable KPIs for each of the some traditional perspective (customer and finance).	Visually very cluttered and messy,making it hard to navigate it and use it as a support to make decisions; the over complexity make the tool lack precision; redundant KPIs make the interpretation quite difficult.	Not recommended for organizations were simplicity is preferred; does nos correspond to non-profit organization, nor non-governmental organizations; discouraged for organizations with a small focus on sustainability; not recommended for quick interpretation needs.

Table 3.6: Summary of the four SBSC architectures comparison

Moreover, the comparative analysis of the four SBSC architectures reveals key insights that not only enrich our understanding but also set the stage for future research and discussion.

3.6.2 Challenges and adaptations in KPI classification

Two interviews brought into focus the complexities of categorizing an organization's KPIs within the traditional BSC perspectives: finance, customer, internal business processes, and learning & growth, as well as the additional sustainability perspective. This task proves challenging, especially when these predefined categories don't fully correspond with an organization's core activities or when particular KPIs don't neatly fit within these categories.

Irrespective of the architectural model selected, solutions emerge that involve either adopting more context-appropriate terminologies or introducing sub-categories within the existing perspectives. These changes, although deviating slightly from the traditional BSC model, are generally seen as beneficial for the SBSC's successful implementation within an organization. Such adaptations make the SBSC more custom-tailored and effective, enabling a more nuanced capture and measurement of strategic objectives and performance metrics.

Significantly, none of the respondents advocated for the complete removal of perspectives from the SBSC. Instead, they emphasized the value of maintaining this structural framework. Despite its limitations in perfectly aligning with all KPIs, the perspectives serve as a useful organizing tool. Respondents felt that these perspectives facilitate a structured and multifaceted approach to performance evaluation, aiding in both strategy development and effective communication. This viewpoint underscores the continued relevance of the BSC structure, even as there is a clear need for customization to suit an organization's unique requirements.

3.6.3 Contextual adaptations in SBSC architecture

While it is widely acknowledged that the BSC should be context-sensitive to fit an organization's unique needs (Lueg & Carvalho e Silva, 2013), this principle is equally applicable to the SBSC. Customizations may be necessary to reflect the organization's distinct priorities, which can vary based on the industry, activity, and contextual factors (Chaker et al., 2017). Hence, the choice of an SBSC architecture could very well be influenced by these variables.

Adapting to organizational context

In the interviews, the majority of respondents highlighted the challenges of making the traditional four BSC perspectives conform to their organization's unique set of priorities. At skeyes, for instance, any tool they develop is highly customized to align with the company culture, often resulting in a final product that diverges substantially from the traditional model. For an SBSC to be effective, it must resonate with the organization's core principles. This enables those who use the SBSC tool to better understand and identify with their business, thereby facilitating its adoption and effective use. Therefore, when crafting an SBSC, it's crucial to factor in the organization's vision, mission, culture, among other elements. Future research should focus on outlining the key steps required for fine-tuning an SBSC to a particular organizational context.

Adapting to industry context

Beyond the scope of individual organizations, the SBSC can also be customized to fit the nuances of specific industries, thereby increasing stakeholder comfort and alignment with daily business activities. For instance, Khalid et al. (2019) provides a framework for integrating the SBSC within the healthcare sector. Going forward, more research could explore how the SBSC framework can be adapted to suit various other industries, thereby increasing its applicability and effectiveness across different sectors.

Adaptations for audience and purpose

As one respondent pointed out, the selection of the most appropriate SBSC architecture could also be contingent upon the audience it is intended for, as well as its primary objectives. Depending on the complexity level desired, certain elements may need to be simplified or emphasized. For example, the Extended architecture was deemed highly effective for generating a thorough and accurate overview but was not considered ideal for conveying the SBSC in a straightforward manner ("*I would have trouble getting myself understood*"). Consequently, this architecture might be most suitable for strategic departments requiring an in-depth, top-down view.

However, when the objective is to communicate key insights to high-level executives or operational teams, a more simplified version may be more effective. This could involve adopting one of the other available SBSC architectures that are less complex and more straightforward. This adaptability serves to underscore that the choice of SBSC architecture, or its subsequent modifications, should be closely aligned with the tool's intended purpose and target audience. Future research may benefit from exploring this dynamic further, aiming to align different SBSC architectures with specific audiences and purposes.

3.6.4 Visual SBSC output should be decomplexified

In general, the visual representations of the four SBSC architecture types were perceived as quite complex. In fact, several respondents explicitly expressed their lack of confidence in explaining the SBSC during a meeting, and some went so far as to indicate that they would not attempt to present it at all. However, the respondent did bring up several suggestions to simplify the output of the SBSC, including the following: clustering the indicators inside the perspectives, establishing sub-perspectives or skimming down the number of causal relationship through human expertise.

While there are no strict guidelines regarding the quantity of measures that should be included in each perspective, attempting to include too many measures can prove to be overwhelming and divert focus from the company's primary strategy (M. J. Epstein & Wisner, 2001). As this issue poses a significant concern since the lack of clarity can hinder the effective utilization of the SBSC in strategic DM, simplifying the visual output of the SBSC seems therefore a worthwhile further research endeavour.

3.6.5 The pitfalls of data-driven SBSC

The interviews have shed light on the limitations of a purely data-driven approach to build SBSC, as certain respondents expressed skepticism regarding some cause-and-effect links, particularly those who were directly or closely involved in operation activities. Consequently, organizations, when employing data analysis, may opt to refine the generated results by incorporating insights from their in-house business experts, thus strengthening the causal chain and obtaining a more robust SBSC. This remark was also highlighted by Pirnay and Burnay (2022).

Data can sometimes pose a significant obstacle when crafting a robust SBSC. This challenge becomes evident in our case study, where some KPIs exhibit seasonality, as it is common in the aviation industry. Seasonal variations can render some time series data non-stationary, potentially leading to inaccuracies in analysis and implying careful interpretation. While in our case study, the primary objective was to construct four SBSC models for a comparative discussion of their strengths and challenges, the importance of quality and reliability of data and data analysis cannot be understated when designing a strategic DM support tool to be used in practice.

Previous research has explored ways to make intuitive-building BSC more robust by means of, for instance, fuzzy-methods (see Chytas et al. (2008), Jassbi et al. (2011), and Mohamadnejad and Jassbi (2012), among others). On the contrary, additional research should focus on investigating methods to enhance the resilience of data-driven BSC, thereby enabling the development of a resilient SBSC.

3.6.6 Integration of the SBSC with other sustainable tools

While the SBSC, when fully implemented to achieve its application goals, remains comprehensive, it may also be advantageous to develop it combination with other tools. For instance, the SBSC could be develop jointly to a materiality assessment in an organization. Materiality assessment involves identifying and prioritizing important environmental, social, and governance issues that significantly affect a company and its stakeholders (Guix & Font, 2020). The materiality assessment and SBSC serve different purposes. The assessment identifies what's most important in sustainability, while the SBSC provides a structured way to track, measure, and manage these material issues within the broader strategic framework. The SBSC and materiality assessment can work together in a dynamic and synergistic way, complementing each other to improve the effectiveness of sustainability management within an organization, rather than one being a subset of the other, as seen in the literature (Guix & Font, 2020).

Similarly, the SBSC has the potential to be collaboratively developed with other sustainable tools such as Life Cycle Assessment, the Triple Bottom Line (Junior et al., 2018; Kaplan & McMillan, 2020), or Sustainable Development Goals (Kato et al., 2017), forging strategic partnerships that enhance its efficacy in tandem with diverse methodologies, ensuring a comprehensive and adaptable approach to sustainable business practices.

3.6.7 Paving the way for other types of BSC

As slightly introduced in the foreword of this Chapter, the output of this study could open the discussion on other modifications of the BSC. Indeed, the four architectures of the BSC designed to enhance sustainability can be effectively adapted to various organizational contexts beyond environmental concerns. For instance, we can imagine an organization aspiring to optimize its Information Technology (IT) performance or Human Resources (HR) management could employ specialized versions like IT-BSC or HR-BSC. Similar to SBSC architectures, such as add-on, extended, separated, and integrated, these adaptations can facilitate a structured approach to incorporating the specific KPIs of each concept. Consequently, the conclusion of our study, derived from sustainability-focused BSC architectures can offer valuable guidance in tailoring the BSC to diverse organizational needs, fostering a comprehensive approach to performance measurement and strategic management.

While the adaptability of the BSC could also allow for the incorporation of multiple concepts simultaneously, caution must be exercised to avoid information overload and ensure the tool remains a practical decision-making resource. For instance, an organization might consider developing a Sustainable-IT BSC to holistically address both sustainability and information technology performance. However, as discussed earlier, even a single modification to the traditional BSC architecture can pose challenges in terms of visual clarity and usability. When integrating multiple concepts, such as sustainability and IT, it becomes imperative to strike a balance between comprehensive insights and practical usability. To overcome potential challenges associated with information overload, organizations could explore dynamic online tools with filtering capabilities. These tools enable users to customize their views based on specific criteria, ensuring that decision-makers can focus on relevant information without feeling overwhelmed by the amount of information.

3.7 Limitations

Certain limitations need to be considered when interpreting the results of the present study. One significant factor for study I is that all of skeyes' current sustainable indicators belong to the customer perspective, mainly because the organization's sustainable transition is relatively recent, and historical data for other sustainable KPIs suitable for data-driven analysis is not yet available. This could have made the integrated architectures less appealing in this specific case study. In the future, skeyes intends to incorporate a broader range of sustainable KPIs which could potentially differentiate more one architecture from another. Additionally, it's worth noting that the sustainable KPIs utilized in this study were primarily operational in nature, and this may not hold true for all organizations. In study II, the reliability of the results are subject to the quality of the eight focus group and the interpretability of the research authors. Conducting a larger study would enable us to validate and generalize our results more effectively.

Another important limitation in this Chapter concerns the purpose of building a SBSC: signalling or greenwashing? The present study did not focus on the potential greenwashing aspects of sustainable performance disclosure, as suggested by Mura et al. (2018). Authors Hahn and Figge refutes the connection between the adoption of the SBSC framework and a company's readiness to assume accountability for sustainable issues (Hahn & Figge, 2018). They illustrate their argument by citing the case of oil companies that, as of 2018, denied climate change while simultaneously incorporating environmental factors into their BSC. Hence, it raises the question of whether the SBSC might be employed as a tool for greenwashing in an increasingly environmentally-conscious world or if, conversely, the SBSC can serve as a lever to signal (Connelly et al., 2011) to stakeholders (both internal and external) the sustainability efforts of their organizations. Greenwashing in the context of the SBSC can be defined as "*[the usage of] sustainability reports to portray [firms] as 'good' corporate citizens, despite not having any particular social or environmental credentials*" (Mura et al., 2018, p.681). A further study could try to explore the likeliness of using the SBSC for as signalling or greenwashing purposes and on ways to detect and prevent the latter.

3.8 Conclusion

We begin this study by laying the conceptual foundation of corporate sustainability as a precursor to our in-depth exploration of the SBSC. Through a comprehensive review of existing literature, we highlighted the core principles and identified limitations of the SBSC framework, underscoring that it does not serve as a panacea for strategic planning.

Guided by our three research questions, we adopted a methodological approach that entailed the creation of four different SBSC architectures utilizing operational data from skeyes. These models were subject to rigorous qualitative analysis via semi-structured interviews with skeyes' professionals, providing us with valuable expert opinions on the relative merits and shortcomings of each architecture.

The interview results were meticulously examined and discussed, leading us to summarize the key attributes and functionalities of each proposed architecture. These insights paved the way for a multi-faceted discussion on the SBSC, thereby contributing to our broader understanding of the framework and inspiring several avenues for future research.

Our findings emphasize the importance of context in SBSC architecture – be it organizational, industry-specific, or dependent on the audience and purpose for which the tool is intended. Future research could delve deeper into the process of tailoring SBSC architectures to specific organizational or industry needs and further explore the interplay between the choice of architecture, audience, and intended purpose.

Chapter 4

Finding Common Ground Through a Hybrid Approach

Foreword of Chapter 4

The first Chapter of this dissertation demonstrated that SMs were primarily designed based on soft data. The second and third Chapters showed that they could encounter issues and proposed a way to construct them using hard data. During interviews with experts from organizations, it was noted that this data-driven approach also has flaws. Therefore, it seems evident to have a third and last *design cycle* in our DSR methodology which could offer a final artifact for the design of SMs: hybridization (Figure 4.1). This final design cycle is based on the knowledge base from all previous Chapters, the literature on intuition analysis. The practical environment surrounding this cycle is composed of experts from all types of organizations and skeyes experts and data as case study once more.

This final Chapter is the culmination of this dissertation and presents a methodology for designing SMs based on both hard data and expert intuition, including a process for managing the tensions that may arise during the integration of these two types of analyses. This last Chapter is a joint work with Prof. Corentin Burnay and is associated to a finished paper entitled "*From 'Data vs Intuition' to 'Data ft Intuition' – A Framework to Design Hybrid Decision-Making Tools*".

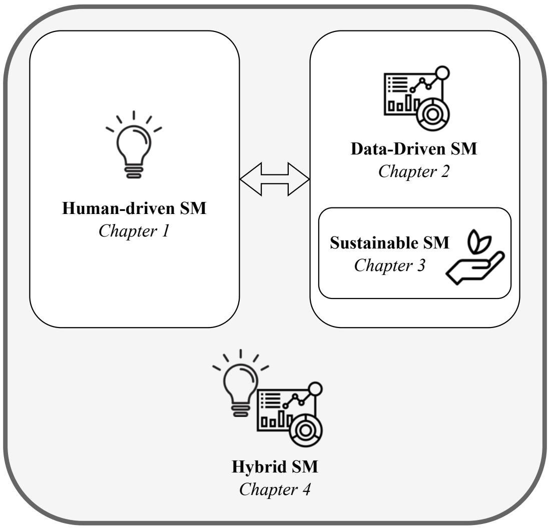

Figure 4.1: Positioning of Chapter 4 in the thesis

4.1 Introduction

In today's fast-paced business world, organizations must aim for success, and the speed and quality of decisions play a crucial role. Managers are tasked with making choices that directly affect their companies' value and thriving capacity, placing a significant burden on them to make optimal decisions (Rode, 1997; Vroom, 1973). DM is the process of selecting the best course of action among multiple alternatives, often involving a complex evaluation of factors, risks, and consequences (Bazerman & Moore, 2012). To help individuals and organizations in making informed decisions, a range of DM tools and methodologies have been developed. For instance, the BSC, the SWOT matrix, the Total Quality Management, Six Sigma or the Objective-Key Results, are among the most famous tools to help decision-makers support their decision. These tools can provide structured frameworks for decision-makers, ultimately facilitating more effective and well-informed organizational choices.

Initially, DM predominantly relied on human intuition, where experienced leaders used their expertise and gut feelings. As the world became increasingly globalized and complex, coupled with rapid technological advances, organizations shifted towards a more data-driven approach

(Bryndjolfsson & McElheran, 2016a). This transition allowed for more informed and evidence-based decisions. However, as technological advancements (particularly in fields like artificial intelligence) accelerated, DM processes became somewhat opaque, impersonal, sometimes raising ethical concerns. It is clear that there is an urgent demand to transition towards hybrid DM systems that harness the benefits of both human intuition and data. This approach is essential for enabling managers to make informed decisions while upholding principles of accountability, transparency, comprehensibility, and ethical responsibility throughout the DM process.

This Chapter examines two distinct approaches to DM: intuitive and data-driven. Intuitive DM involves choices made by decision-makers relying on instinct, gut feelings, implicit knowledge, or experience. In contrast, data-driven DM refers to choices made based on empirical evidence supported by data analytics and statistical analyses. We posit that each approach has its own merits and drawbacks, and we advocate for DM tools that effectively integrate both methodologies. The current literature however does not provide with processes to build such hybrid DM tools. In response to this challenge, this article proposes a methodology to design hybrid DM tools, giving rules on how to combine outputs from data and intuition whenever tensions arise. The resulting artifact is our Data-Intuition Integration (DII) framework. Hence, our research objectives can be described as follows:

- **Research objective 1.** Elicitation of the requirements to build a usable, up-to-date, and hybrid DM tool for decision-makers.
- **Research objective 2.** Developing a design methodology that meets the key/critical requirements.

To fulfill these objectives, we employ a Design Science Research (DSR) research methodology to formulate an integrated hybrid framework encompassing both intuition and data. The artifact acknowledges the equal significance of human judgment and empirical data in the DM process, recognizing the inherent advantages and pitfalls associated with each. This approach empowers the DM tool to yield insights that are more reliable and accurate, thereby enhancing the ability of organizations to make informed and improved decisions.

4.2 Background

DM is a fundamental aspect of management that impacts an organization's performance. Managers make decisions daily, from small operational choices to significant strategic ones. These choices can have a big impact, so understanding how to make good decisions is crucial. In DM, there are common steps to follow, such as identifying the problem, gathering information, evaluating options, making a choice, and assessing the results (Bazerman & Moore, 2012). Managers also have different DM styles, from 'gut feeling' (Sadler-Smith & Shefy, 2004) to data-driven approaches (Brynjolfsson & McElheran, 2016b).

In the DM literature, intuition has been extensively examined, as evidenced by previous research (see Dane and Pratt (2007)), and is not a novel concept. Herbert Simon articulated in 1987 that individuals often make judgments swiftly, bypassing a systematic analysis of the situation (Simon, 1987). This expeditious DM process is facilitated by the selective processing of essential information, resulting in time savings (Burke & Miller, 1999). Recent investigations in sports DM align with the notion that intuition enables rapid DM (Raab & Laborde, 2011). Studies on decision heuristics indicate that, at times, neglecting certain information can lead to more accurate judgments than attempting to consider the entirety of available information (Gigerenzer & Gaissmaier, 2011). Moreover, intuitive DM is lauded for its adaptability in unpredictable environments. Khatri and Ng (2000) observed the prevalence of intuitive processes in organizational DM, noting that reliance on intuition positively impacted organizational performance in unstable environments but bore negative consequences in stable ones (Khatri & Ng, 2000). It is imperative to acknowledge that even experts are susceptible to errors in judgment. Tversky and Kahneman introduced the concept of bias resulting from judgment heuristics in 1974 (Tversky & Kahneman, 1974). Another crucial consideration is that intuitive DM is not inherently consistent and can be influenced by various factors, including specific organizational characteristics (Elbanna & Fadol, 2016) and the emotional state of the decision-maker (S. Epstein, 1998).

On the other hand, the current era of business has been marked by an exponential growth of data, and organizations have been using a variety of tools and techniques to harness the potential of this data. The emergence of data (mining) analytics for strategic DM, coupled with following advancements in information technology around the year 2000, has given rise to a landscape characterized by both challenges and opportunities in the field of strategic DM (Nazem & Shin, 1999). Previous research strongly suggests that using analytics is closely linked to an organization's growth (Davenport & Harris, 2007). In simpler terms, having more data and better analytics can help companies make better decisions, ultimately improving their performance (Mithas et al., 2011; Sharma et al., 2014). Ghasemaghaei et al. (2018) found a positive relationship between data analytics competency and firm DM performance. However, as technology is getting more complex, decision support systems have been constructed as 'black boxes' (Guidotti et al., 2018). This can hinder the utilization or trust toward the tool and lead to a disengagement (Rai, 2020).

The synergy of rationality and intuition has been shown to contribute to successful strategic DM (Thanos, 2022). The fusion of data and intuition has been explored, primarily in the field of artificial intelligence, with Jarrahi (2018) advocating for intelligence augmentation and emphasizing the complementarity of human and artificial intelligence. Furthermore, Shrestha et al. (2019) conducted a comparative analysis between human and AI-based DM, evaluating them across key dimensions such as specificity of the decision search space, interpretability of the DM process and outcome, size of the alternative set, DM speed, and replicability. Their findings underscore the potential for integrating both modes of DM, proposing hybrid and aggregated solutions to effectively address these dimensions. The essence of strategic DM lies in harnessing the collective capabilities of human and artificial intelligence to provide enhanced solutions for navigating complex scenarios proficiently (Pratt et al., 2023). However, existing studies have predominantly focused on artificial intelligence, surpassing our specific emphasis on data. To the best of our knowledge, no study to date has explored the integration of these two elements while confronting inherent tensions.

Navigating the difficulties of strategic DM poses a contemporary challenge for managers, necessitating the harmonious integration of human intuition and data-driven analysis. We have identified a number of challenges and opportunities of both intuition and data (see Guidotti et al. (2018), Jarrahi (2018), Khatri and Ng (2000), Shrestha et al. (2019), and Tversky and Kahneman (1974)), summarized in Table 4.1. The table outlines the hurdles faced by intuition and demonstrates how data analytics can serve as a valuable counterbalance. In this context, the interplay of human intuition and data analytics emerges as a tandem, providing managers with a comprehensive toolkit for addressing the multifaceted challenges of strategic DM.

Challenges of Intuition	*mitigated by*	**Opportunities of Data**
Prone to biases	→	Consistent, highly replicable
Time consuming when numerous people involved	→	Automated, Fast
Analytical limitations	→	Scalable
Internal view	→	External integration
Challenges of Data	*mitigated by*	**Opportunities of Intuition**
Perform better under normal circumstances	→	Flexible, adapted to unstable environment good under uncertainty
Low adoption	→	Embodied
Black Box effect	→	Explainable and interpretable
Impersonal	→	Personalized, with ethical considerations

Table 4.1: Potential complementarity of intuition and data for DM

4.3 Research methodology

Throughout this Chapter, we carry out a full DSR cycle (Hevner, 2007; Hevner et al., 2004) to iteratively build and evaluate our final artifact, the DII framework. We follow the DSR steps proposed by Peffers et al. (2007) to structure the remainder of the Chapter (see Figure 4.2).

Section 4.4 introduces ten design requirements obtained from interviews with DM experts. These requirements form the foundation for the development of our artifact and serve as a benchmark for comparing our solution to existing alternatives. Section 4.5 details the design process of our artifact, culminating in the description of the final DII framework. Then, Section 4.6 offers a comprehensive demonstration of the proposed framework in a real-life setting, illustrating its practical applications and enhancing the following discussion. Lastly, Section 4.7 assesses both the validity of the DSR process and the resulting artifact.

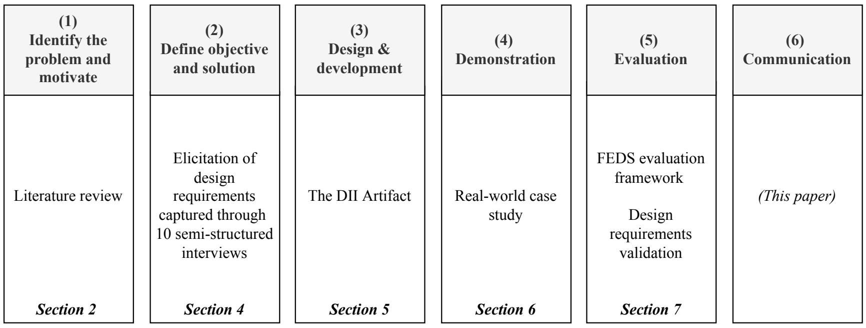

Figure 4.2: DSR framework adapted from Peffers et al. (2007, p.54), applied to this study

The possible type of contribution of a DSR work differs based on the research requirement (Baskerville et al., 2018) and the maturity of existing solution and field (Gregor & Hevner, 2013). In the present study, we aim to construct and evaluate an innovative artifact. The representation of the artifact (see Section 4.5) and the demonstration of its novelty and its practical improvements (see Section 4.7) are required to position our contribution (Baskerville et al., 2018). Despite the high maturity in our application domain, marked by extensive exploration and study of DM tools, data analyses, and intuition analyses, the specific solution maturity addressed by our artifact – the integration of data and intuition and the resolution of tensions between the two – remains relatively low. Consequently, our artifact falls within the category of an 'improvement' type, as classified under "*New Solutions for Known Problems*" (Gregor & Hevner, 2013, p.346). In this context, there is a compelling need to delineate how and why the proposed solution distinguishes itself from existing alternatives, a discussion expounded upon in Section 4.7. The evaluations conducted on this improved artifact are poised to contribute valuable knowledge, deepening our comprehension of core theories and potentially catalyzing the evolution of new behavioral theories pertinent to the artifact's application.

4.4 Define objective and solution

Our investigation centers on identifying the fundamental attributes deemed crucial by performance and strategy managers for the development of a hybrid framework. To achieve this, we conducted semi-structured interviews utilizing an interview guide designed for the purpose. The interview guide incorporates open-ended questions and employs projective techniques (Pellemans, 1999), including role-playing, to facilitate in-depth discussions. The outcomes of these interviews serve as a valuable compass in the following design phase of a pertinent artifact, enabling the extraction of critical design requirements (DR).

The participants were recruited for the interviews through an invitation letter via direct email. This letter contained a brief introduction of the researchers and to the study, without giving out its final goal. All interviews were virtually held on Teams, Google Meet or Zoom and the audio and video were recorded with the agreement of the participants. The final sample is composed of 10 people after which a saturation threshold was reached in the responses. In order to increase the reliability of our research, the ten interviewees are heterogeneous with respect to: the organization's size, the organization's sector, the type of organization (private or public), the gender of the respondent, the professional position of the respondent (see Appendix 1 for a descriptive table of the sample).

All interviews are entirely transcribed including every hesitation, laugh and blank moments in order to keep the information as genuine as possible. The interviews are analyzed by adopting a deductive and inductive approach. We follow the recommendations of Strauss and Corbin (1990) and apply coding to our interviews transcripts for the analysis. The codes are derived from the literature review, the interview guide themes and the personal knowledge of the researchers on the subject. More codes emerge from the interviews transcripts and are added to the initial list.

Based on the qualitative interviews, we identified 10 DR to design our artifact, which are summarized in Table 4.2. The interviews extracts justifying the definition of these DR are presented in Appendix 2. The DR will serve as a basis and will be translated into features for our artifact, it will also ensure its reliability or the adoptability.

4.5 Design and development

In this phase of the DSR, we design our artifact, the final DII framework. Figure 4.3 summarizes the construction of our DII framework.

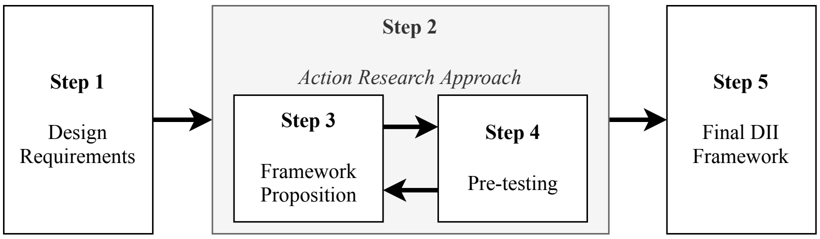

Figure 4.3: Construction steps of the DII framework

Step 1 is the elicitation of the design requirements by relevant stakeholders. In total, 10 design requirements have been captured and presented in Section 4.4. These DR provide the basis of construction of our DII framework.

Step 2 constitutes the core step for the construction of our artifact. This step was conducted using an action research approach, as referenced by Avison et al. (1999), in cooperation with two organizations, the Belgian Air Traffic Control Company and a conglomerate of 4 Belgian University Hospital Centers. Action research is a pragmatic methodology centered on addressing tangible real-world challenges and effecting enhancements within a particular setting or organization. It involves the collective efforts of a team of practitioners to identify issues, devise solutions, test them, and evaluate their impact. In order to ensure the relevance and effectiveness of our artifact in practical application, it was

Design requirements	Definition
DR1: Include intangible measures	The framework can take into account non-material or non-physical aspects that are difficult to measure in concrete terms.
DR2: Include external data	The framework relies on or incorporates information or inputs from sources outside of the immediate system or organization.
DR3: Quality data	The framework runs on data that is accurate, reliable, and free from errors or inconsistencies, ensuring its trustworthiness and suitability for making informed decisions.
DR4: Isolate key information	The framework enable the extraction and focus on the most crucial and relevant data or elements while disregarding or minimizing less important information.
DR5: Rapid/Real-time	The framework operates with minimal delay, providing immediate or near-instantaneous analyses or guidance.
DR6: Interoperability	The framework can seamlessly work and communicate with other systems, software, or components of the organization.
DR7: Output stability	The framework helps maintain consistent and reliable results or responses, reducing variability or unpredictability.
DR8: Interpretability/Comprehensibility	The framework allows users to easily understand and explain how the framework's processes or decisions are made.
DR9: Aligned with mission/vision	The framework goal and output are consistent and supportive of the overall purpose and long-term objectives of the organization.
DR10: Integrating both data and intuition	The framework should include both analysis outputs from data and from intuition of experts of the organization.

Table 4.2: Summary of retrieved requirements from interviews

imperative to engage with experienced professionals. By confronting our developments with the insights and expertise of those actively engaged in the field, we were able to validate the practicality of our methodology and identify potential issues that could hinder its successful implementation. This action research perspective and corresponding interactions with professionals not only served to bridge the gap between theory and practice but also offered valuable feedback that enabled us to refine our approach. This collaborative effort allowed us to create a more robust and applicable solution, one that could effectively address real-world challenges and ultimately enhance the successful implementation of our methodology. This step is further decomposed in two, iterative steps.

Step 3 and 4 are back and forth steps to design our artifact. From proposing to pre-testing (parts of) our framework iteratively, to come up with a final, robust DII framework. Each of these steps was confronted to real-life application and discussed deeply with the Performance and Strategic Manager of skeyes to ensure practical relevance.

Step 5 results in our final artifact. The final designed DII framework, known as the *Data-Intuition Integration framework* (Figure 4.4), comprises four general phases. It illustrates a process for carrying out a hybrid data-intuition analysis and proposes a process for resolving tensions that may arise when confronting results, between data analysis and the intuition of organizational experts.

The DII is a general process, and we intentionally avoid any normative specifics. We do not propose a specific methodology for data or intuition analyses at this stage, as the most suitable approach depends on the specific context. This flexibility allows for a customized approach that fits the unique requirements of each scenario. However, we have identified several methodologies that could be considered, and the choice will be determined based on the unique requirements and circumstances of the situation. For the intuition analysis, the methodologies which are suitable are interviews, Delphi method, focus groups, surveys and questionnaires, or brainstorming sessions. For the data analysis, correlations, ordinary least square regressions, time series analysis, or machine learning, among others. The choice of methodology depends on the data characteristics, the organizational context, and the competencies of the organization.

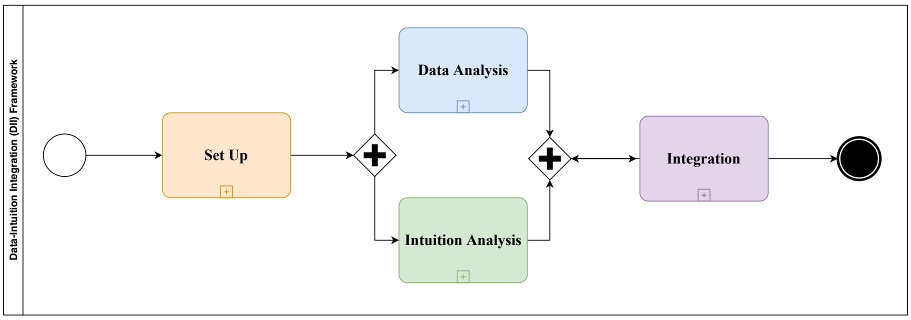

Figure 4.4: Data-Intuition Integration (DII) framework

The set-up phase main's objective is to determine the selection of KPIs to include in the DM tool (Figure 4.5) before going on with the two types of analyses. This is done by first defining the objectives of the tool, then identifying relevant KPIs from both internal and external contexts. Then, the artifact proposes a process in two parallel paths: one for data analysis and the other for intuition analysis. This choice of parallel paths arises from the distinct methodological treatments and analytical requirements demanded by each type of information source. The data analysis path necessitates analytical expertise and computational capabilities, while capturing human intuition involves employing a different methodology.

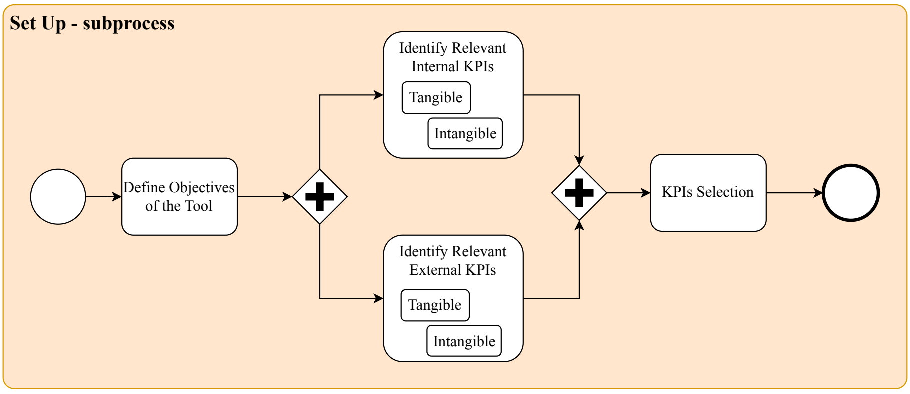

Figure 4.5: Set Up step subprocess

The data analysis phase is composed of traditional data mining steps borrowed and adapted from CRISP-DM model (Wirth & Hipp, 2000). Indeed, while the three other steps of our framework lack background foundations, this phase has already been largely investigated in the literature. However, we adapted it and created a subprocess presented in Figure 4.6. First, there is a need to check the availability of the data, related to the selected KPIs from the previous phase. Then, the data collection and pre-processing are undertaken. Finally, the data analysis methodology is carefully selected, based on the DM tool objective and the data prerequisites. This step is left out as generic because it needs to be adapted to each context. The data analysis phase ends with the application of this appropriate methodology.

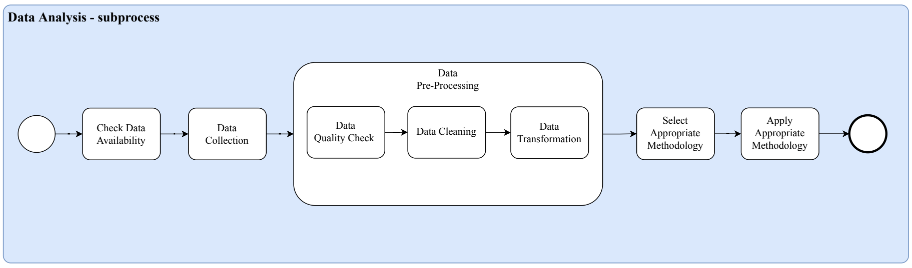

Figure 4.6: Data Analysis step subprocess

The intuition analysis phase gathers all steps for collecting and analyzing the intuition of experts of the organization. Contrarily from the previous step, the way to collect organizational experts' intuition on a topic is not well documented. Many authors have studied the mental process that each person goes through while making a decision (see the work of Langley et al. (1995) or Klein (1993)). However, the collective collection of intuition in DM is scarce. As this is an equally important step as the data analysis one, we develop a methodology depicted in Figure 4.7 based on an adapted version of the DEMATEL and DELPHI process. Both DEMATEL and DELPHI are used to facilitate group DM and to structure complex problems. The selection of experts is an important step of this subprocess, as it is imperative to have knowledgeable people of the organization to create a robust DM tool. Similarly to the data analysis step, the choice of methodology to employ remains undecided for the same reasons outlined earlier.

Lastly, *The integration phase* is the most challenging phase. It aggregates the outcomes of both analyses, harmonizing and integrating

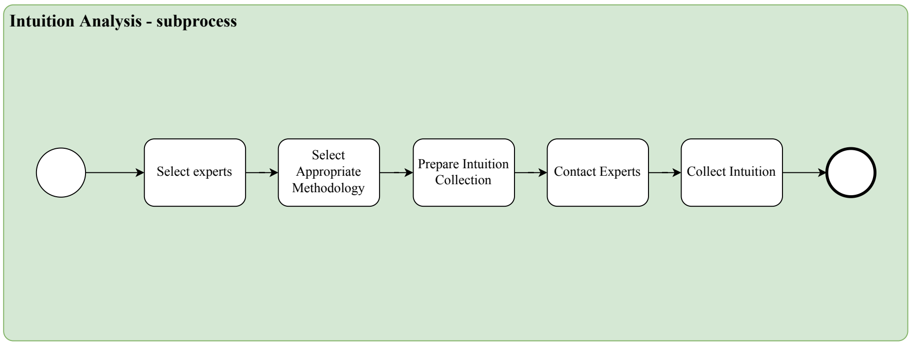

Figure 4.7: Intuition Analysis step subprocess

them to construct a hybrid DM tool reinforced by the insights derived from both data-driven and intuition-based analyses. It appears to be quite difficult to consolidate the two analytical outputs. Integrating the outputs from hard data and soft data analyses presents three distinct possibilities. First, there may be non-conflicting results where the causality between the KPIs is (not) verified by both analyses. This scenario establishes a strong foundation for decision-making, as the alignment between hard data analysis and expert intuition reinforces the reliability of identified relationships. On the contrary, conflicting situations may arise when the hard data does not align with the experts' intuition or when the experts disagree with the data-driven results. These tensions highlight the disparities between data-driven insights and the organizational intuition. As an illustrative example, certain interrelationships between indicators can be presumed to exist by the organization's experts but may not be substantiated by the data analysis. Conversely, the data analysis may reveal associations that appeared counter-intuitive or entirely absent from the experts' perspective.

Balancing these conflicting scenarios requires careful consideration of the strengths and limitations of each data source. Striking an optimal balance involves understanding when to prioritize empirical evidence and when to rely on the nuanced insights of domain experts. Addressing conflicts through iterative analysis and collaboration can contribute to a more comprehensive and nuanced understanding, enhancing the overall quality of decision-making processes that integrate both hard and soft data. The imperative to design a sub-process to resolve these underlying tensions became evident. We found it necessary to establish a systematic process for merging the two outputs, resulting in the creation of a highly resilient and comprehensive DM tool. We propose a process that is easy to put into place, less costly and easily replicable in other conditions. The process offers three possible final DM tool outputs, depicted in Figure 4.8 and described below.

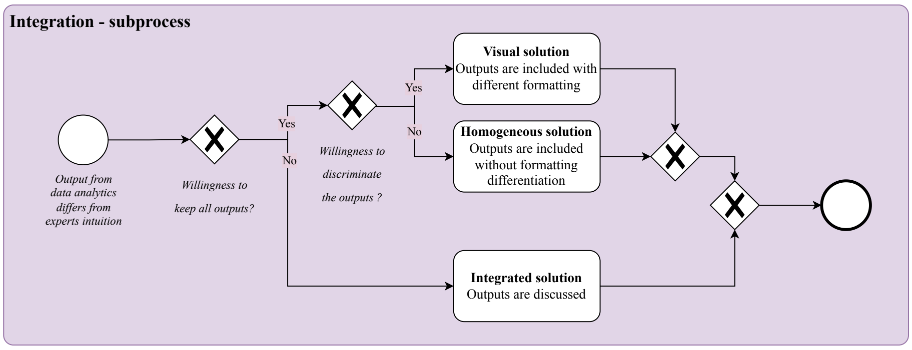

Figure 4.8: Integration step subprocess

1. The ***visual solution*** occurs when disparities arise between the outcomes derived from data and the insights of experts, and the decision-makers are inclined to distinguish between these two analytical outputs. The visual presentation of the DM tool, complemented by a legend, facilitates a comprehensive examination of the results, helping in the discernment of whether they originate from data-driven sources or intuitive judgments;

2. The ***homogeneous solution*** enables the comprehensive visualization of both analytical outputs within the DM tool. However, it does not enable the distinction between the outputs derived from the data and those based on intuitive judgments. This solution helps in preventing bias toward one output over the other;

3. The ***integrated solution*** considers that there is only one single truth and that either the data output or the intuition output is true. Thus, in this case, a resolution of the tension is required.

This solution does not discriminate and display the output's origin as both output are considered correct and the integrated solution present all 'true' outputs. In this purpose, we propose to carry out a DELPHI study (Linstone, Turoff, et al., 1975) to reach a consensus of which result should be included or not in the final DM tool. Conducting a DELPHI study involves giving more authority to experts, primarily relying on their intuition, which aligns with the fact that they are the ones who will ultimately use the tool, making this approach logical. Skinner et al. (2015) outlines five key attributes associated with a DELPHI study: the utilization of experts, the formation of a panel, the provision of anonymity, the conduct of multiple rounds and iterations, and the incorporation of feedback. The DELPHI technique proves to be pertinent in this context for several compelling reasons, aligning with the fundamental characteristics of this research methodology. To begin with, the DELPHI technique is renowned for its ability to facilitate the attainment of consensus among experts, a crucial requirement in our scenario. We must ascertain consensus to make determinations when confronted with the choice between deriving outcomes from data or relying on intuition, particularly when tension exists. It is worth noting that a fundamental distinction between a DELPHI study and a conventional survey lies in the iterative process designed to reach a consensus among experts. Furthermore, the DELPHI technique offers a structured and systematic approach that can be implemented asynchronously, presenting a substantial advantage. This feature proves invaluable as the process of gathering opinions from experts may necessitate a considerable amount of time to ensure the participation of all relevant individuals. It is important to clarify that the DELPHI involves a different set of experts than the intuition analysis phase, which avoids redundancy in the answers. Moreover, the question here is not whether the output is correct, but rather whether it should appear in the DM tool or not, without specifying whether the source of the output is based on data or expert intuition.

4.6 Demonstration

We demonstrate the practical implementation of our DII framework in a real-life case study. The first Set Up phase steps is to define objectives and select the strategic framework to build, we employ the design of a SM by Kaplan and Norton (2000) as our primary exemplar DM tool. The SM serves as a compelling illustration of DM tools in a context where both data-driven and expert-driven methods coexist. Introduced in 2000, SMs have emerged as a pivotal performance management tool adopted by organizations globally. Developed by Kaplan and Norton as an extension of the BSC, SM serves to establish causal relationships among KPIs. The SM structure comprises four distinct perspectives: Financial, Customer, Internal Business Process, and Learning and Growth, and it provides a visual representation of these indicators, facilitating an understanding of the cause-and-effects that appear from any given KPI can have within the organization.

Extensive literature has underscored the utility of SMs for organizations, demonstrating their value in strategy formulation, control, and communication (Ittner & Larcker, 2003; Kasperskaya & Tayles, 2013; Malina et al., 2007; Ritter, 2003). Moreover, managers leverage SMs as effective DM tools, helping in both the assessment of external information relevance and strategy appropriateness (Cheng & Humphreys, 2012; Wiersma, 2009).

Traditionally, these maps have been crafted through the lens of human expertise and intuition. However, recent advancements in data analysis have opened up new possibilities. Authors have used techniques that enable the creation of SMs through data-driven analysis, leveraging econometric methodologies. By combining these two approaches, we can apply our DII framework to uncover novel insights and enhance DM.

In this case study, we use operational data provided by *skeyes*. Skeyes is the Belgian air traffic control company that employs 891 people and is responsible for five Belgian airports and two radar stations. In 2022, skeyes guided nearly 900,000 flights safely in the Belgian airspace and at domestic airports and generated revenue of 245.2 million euros in 2021. The use of real data allows establishing the validity, applicability, and generalizability of our proposed artifact in real-world settings.

4.6.1 Set-up phase

Selecting the appropriate indicators is a critical concern for organizations, as it directly impacts the reliability and their trust in the DM tool. When constructing a SM, the meticulous choice of indicators holds significant importance, as both the quantity and quality of these indicators play an important role in the interpretability of the map. Kaplan and Norton advocate for the utilization of 15 to 25 indicators to optimize the efficiency of an SM (Kaplan & Norton, 1996, p. 165).

The primary objective during the setup phase is to finalize the sample of indicators and ensure that they meet the criteria for inclusion in the map. In the context of this case study, we have incorporated a set of 16 KPIs. The process of selecting these KPIs, both internal and external, was the outcome of extensive discussions with experts at skeyes. There was unanimous agreement that these KPIs effectively represent the majority of the organization's business operations.

To gather data for this study, we focused on a specific two-year timeframe, spanning from 2018 to 2019. This choice was driven by the notable disruptions that the aviation sector experienced during 2020 and 2021, attributed to the Covid-19 pandemic and associated lockdown measures. These years are considered non-representative of the organization's standard operational conditions. The complete description of the 16 KPIs can be found in Table 4.3.

4.6.2 Data analysis phase

The choice of methodology for the data analysis phase was to be determined with the specific context of the DM tool to design. In this case, we are designing a SM and thus we are using already developed data-driven approaches. We had a number of methodological options such as Structural Equation Modeling (Saghaei & Ghasemi, 2009), Analytical Hierarchy Process (Quezada et al., 2013), Analytical Network Process (Boj et al., 2014), Linear Programming (López-Ospina et al., 2017), Granger causality tests (Keshavarznia et al., 2020; Kober & Northcott,

ID	Indicator full name	BSC/SM perspective	Short definition
A1	Service Units en-route	Finance	Number of BE-LUX en-route service units
B1	Service Units terminal	Finance	Number of terminal service units at Belgian airports
C2	CDO	Customer	Rate of Continuous Descent Operations flown (reduced thrust and noise, environmental benefits)
D2	En-route flights delayed	Customer	Rate of en-route flights being delayed by skeyes (ATFM delay)
E2	Arrival flights delayed	Customer	Rate of arrival flights being delayed by skeyes (ATFM delay)
F2	Safety operational occurrences (Freq)	Customer	Rate of safety operational occurrences (all severities)
G2	Flight Hours Controlled	Customer	Sum of the flight hours controlled by skeyes units (ACC, APP, TWR)
H2	Movements Airports	Customer	Number of airport movements controlled by skeyes
I2	Movements CANAC	Customer	Number of en-route movements controlled by CANAC
J3	En-route delay per flight	Internal Business Process	En-route ATFM delay per movement
K3	Arrival delay per flight	Internal Business Process	Arrival ATFM delay per movement
L3	Missed Approaches	Internal Business Process	Number of missed approaches at airports
M3	Traffic complexity skeyes	Internal Business Process	Representation of the density of traffic and intensity of potential interactions between traffic
N4	Availability of critical systems	Learning & Growth	Percentage of availability of critical systems supporting ATC operations
O4	Availability of very critical systems	Learning & Growth	Percentage of availability of very critical systems supporting ATC operations
P4	ATCO Hours on Duty	Learning & Growth	Number of hours “ATCOs in OPS” spent on duty in OPS, including breaks and overtime in OPS

Table 4.3: Sample of KPIs for the case study

2021; Pirnay & Burnay, 2022), among many others. We decided to use the latter methodology to produce the data analysis aspect. Indeed, Pirnay and Burnay (2022) provides with a full, replicable data-driven framework which offers insights into the interrelations between KPIs, a choice that aligns with our selection of SM.

In order to estimate the cause-and-effect relationships between the KPIs of an skeyes based on data, we transform our KPI data into a time series. In line with common practice, we ensure data stationarity using the augmented Dickey-Fuller test and select the optimal number of lags based on the Akaike information criterion. Then, we propose the utilization of vector autoregressive (VAR) models and Granger causality tests for the validation of causal links within the indicators of the SM. VAR models, often described as "*the most successful, flexible, and easy-to-use models for the analysis of multivariate time series*" (Zivot & Wang, 2006), offer a comprehensive approach, including the application of Granger causality tests among other structural analyses. The Granger causality test, developed in 1969, serves as a valuable tool for exploring causal relationships within time series data (Granger, 1969). Granger tests go beyond mere correlation by facilitating the detection of causal effects, distinguishing cause from correlation. In this context, causality is inferred based on the predictive ability of one variable for another. Specifically, if the historical information of both X_t and Y_t collectively predict X_t more effectively than the historical information of X_t alone, it is reasonable to conclude that Y_t causes X_t (Granger, 1969). For the interpretation of Granger tests, we adopt a significance level of 5%.

4.6.3 Intuition analysis phase

The choice of methodology for the intuition analysis phase was also let to be determined with the specific context of the DM tool to design. In order to estimate the cause-and-effect links between the indicators of an organization based on expert intuition, we employ the Decision Making Trial and Evaluation Laboratory (DEMATEL) procedure. This choice is motivated by the popularity of this approach to design a SM in the literature. We preferred this methodology to other commonly used in the design of SM such as brainstorming (Ahn, 2001), interviews (De Carlo et al., 2008) or workshops (Papalexandris et al., 2004), among others, because DEMATEL provides a systematic and structured approach which aims to reduce subjectivity by using data and systematic analysis. The DEMATEL methodology is a mathematical procedure originated from the Geneva Research Centre of the Battelle Memorial Institute, was designed to deal with important issues of world societies (Gabus & Fontela, 1972).

The experts were contacted by the Performance Manager of skeyes by email and invited to fill in a double-entry matrix on website specifically conceived for this case study. Experts established relationships based on a scale ranging from 0 to 4, where 0 indicates 'no effect' and 4 indicates a 'strong effect' between pairs of KPIs. Then, the DEMATEL procedure is applied, and can be summarized in 5 main steps: (i) finding the initial direct-relation matrix, (ii) normalizing the initial direct-relation matrix, (iii) calculating the total-relation matrix, (iv) defining degrees of influence and (v) plotting the causal diagram. In order to stay coherent and balanced results with the data analysis, we defined a threshold in step iv. The threshold plays a crucial role in determining the number of relationships that will be considered influential in the final analysis. By setting a predetermined threshold value, decision-makers establish a criterion for inclusion or exclusion of relationships between elements in the system. Elements with total influences above the threshold are considered influential, and their relationships are further explored, while those below the threshold are deemed non-influential and excluded from the detailed analysis. In other words, the higher the threshold is set, the less links will be kept in the SM. In our case, the defined threshold was chosen to yield approximately the same number of causal relationships in our SM and give equal power to both types of analyses without overloading the SM.

4.6.4 Integration phase

The results from both data and intuition analyses are collected, analyzed and compared. Some outputs are in tension meaning that they are verified by either the data or the intuition of the experts but not by both. The last phase of our artifact thus comes into play and the three possible outputs presented earlier in Section 4.5 are illustrated below.

The visual solution

The initial suggested approach is the visual solution, illustrated in Figure 4.9, which consolidates all relationships within the SM. This visual representation enables a comprehensive analysis of the results. The accompanying legend helps in distinguishing whether the results stem from data, intuition, or a combination of both. This visual differentiation can influence the DM process, as it allows decision-makers to consider or disregard the depicted connections based on their beliefs. We arrive with a SM comprising 17 data validated links, 11 intuition validated links and 3 links validated by both analyses.

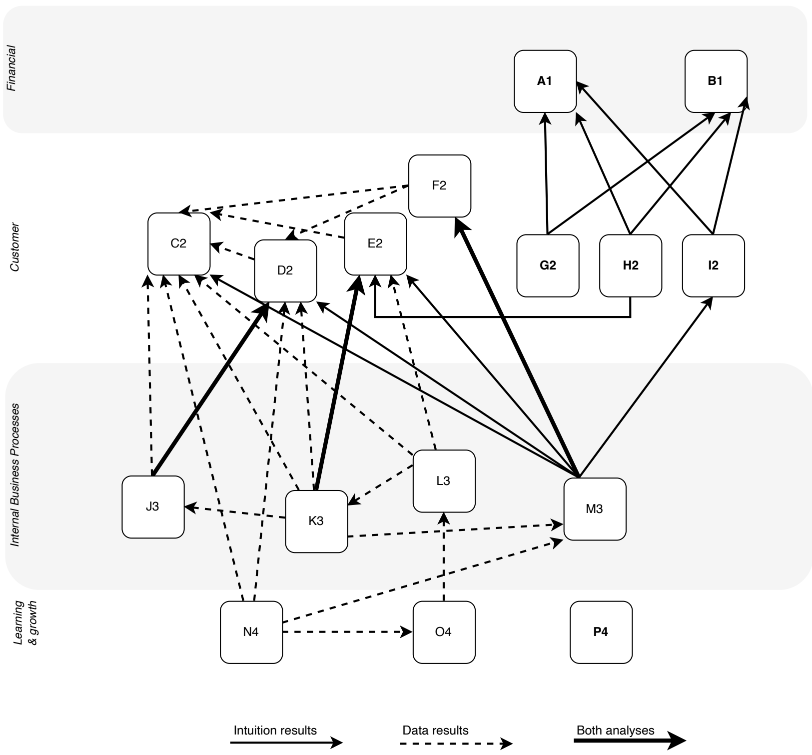

Figure 4.9: Visual solution for the DII

The homogeneous solution

The second solution, referred to as homogeneous (Figure 4.10), similarly presents all results from both analyses. However, it diverges from the previous solution in that it does not allow for the differentiation of the information source that contributed to a specific link result. In this case, we end up with the 31 links SM with indistinguishable sources.

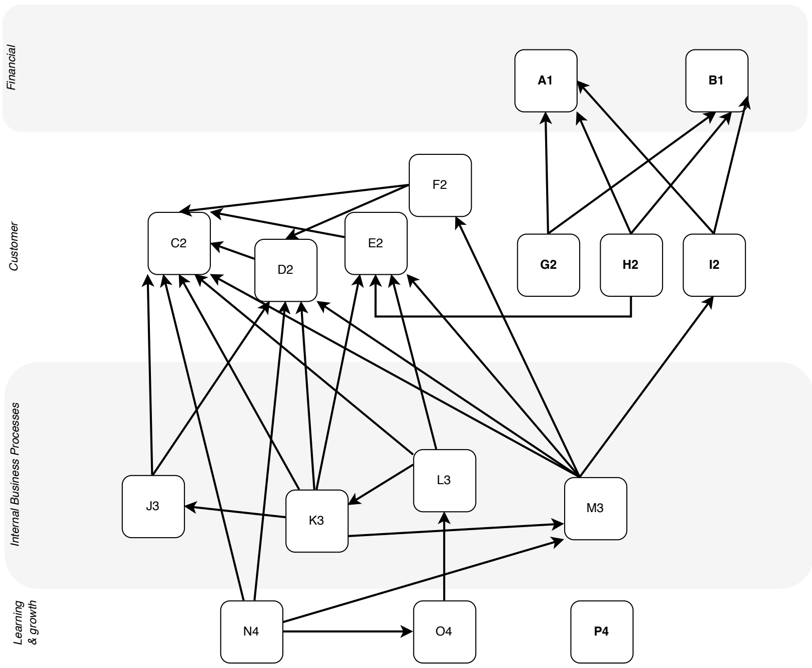

Figure 4.10: Homogeneous solution for the DII

The integrated solution

We observe from the visual solution (Figure 4.9) that few relationships between the indicators of the SM have been validated by both intuition of the expert and data analyses. All the links not in bold are thus hold certain tension between the intuition and the data. We resolve these tension by carrying out a DELPHI study and build the integrated solution.

The participants recruited for this DELPHI study are 3 experts of skeyes organization, who belong to different departments at skeyes. In order to avoid any bias from data or intuition preferences, the source of the links to discuss were disclosed. The DELPHI study took place in two rounds, with iterative feedback. In round 1, the participants were able to assess whether to keep or delete a tension link of the SM based on a 5-points Likert scale ranging from 1 (this link should not be present in the decision-tool) to 5 (this link should be present in the decision-tool). With every answer, the participants were invited to leave a comment to justify their choice. In round 2, the average response of the participants were communicated, individually, to each participant, alongside their previous answer and all justification feedback. The participant could then choose to adapt their answer or keep their previous answer. The DELPHI study was stopped after the second round. Table 4.4 summarizes the results after round 2 of the DELPHI study.

Figure 4.11 depicts the integrated solution resulting from the DELPHI study. We observe that the respondents have decided to delete 11 links (round 2 average score inferior or equal to 3) from previous analysis outputs. The resulting integrated SM thus includes 20 links, those of which are not differentiated from their source of analysis.

4.7 Evaluation

4.7.1 FEDS

To assess our DSR process and the final designed artifact, we adopt the Framework for Evaluation in Design Science Research (FEDS) proposed by Venable et al. (2016). For the functional purpose (the “why”) of our evaluation, we opt for a summative evaluation, ensuring that our final outcome aligns with the initial expectations and requirements. Additionally, we choose a naturalistic environment evaluation, as the paradigm (the “how”) for our evaluation, to appraise the final artifact in a real-world setting. To execute a summative and naturalistic evaluation of our designed artifact, we employ two methodologies: the case study presented in Section 4.6, and validation through the fulfillment of design requirements elucidated by business experts in Section 4.4.

Cause KPI	Effect KPI	Effect Previously Validated by	DELPHI average score after round 2	Relationship will be depicted in the SM?
E2	C2	Data	3,33	yes
K3	M3	Data	4,67	yes
K3	C2	Data	3,33	yes
L3	E2	Data	3,33	yes
N4	C2	Data	4,00	yes
N4	D2	Data	4,67	yes
O4	L3	Data	4,67	yes
F2	C2	Data	2,00	no
F2	D2	Data	2,00	no
K3	J3	Data	1,33	no
K3	D2	Data	1,33	no
L3	K3	Data	2,00	no
L3	C2	Data	3,00	no
J3	C2	Data	1,00	no
D2	C2	Data	1,00	no
N4	O4	Data	1,67	no
N4	M3	Data	3,00	no
G2	A1	Intuition	5,00	yes
G2	B1	Intuition	4,67	yes
H2	A1	Intuition	3,67	yes
H2	B1	Intuition	5,00	yes
I2	A1	Intuition	5,00	yes
I2	B1	Intuition	5,00	yes
H2	E2	Intuition	5,00	yes
M3	C2	Intuition	4,33	yes
M3	D2	Intuition	3,67	yes
M3	E2	Intuition	3,67	yes
M3	I2	Intuition	2,00	no

Table 4.4: Summary of DELPHI study results

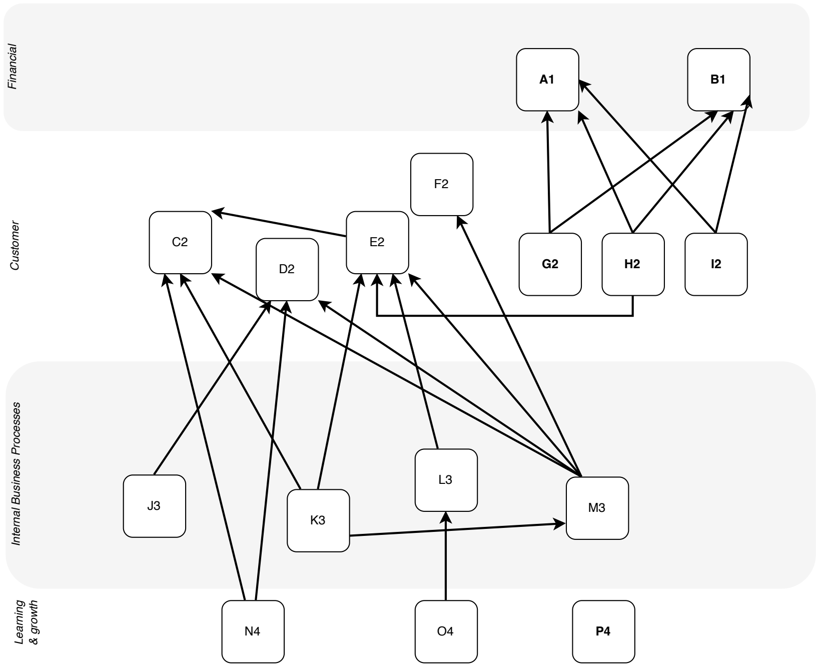

Figure 4.11: Integrated solution for the DII

4.7.2 Design requirements fulfillment

The requirements DR1, DR2 and DR9 are accomplished during the setup phase of the DII framework. *DR1 inclusion of intangible measures* is taken into account in the set up and is made feasible by incorporating expert intuition into the process. When dealing with intangible measures, which can be challenging to quantify, it becomes essential to rely on human intuition and expertise to include these indicators in the DM tool. *DR2 inclusion of external data*, can be achieved through data analysis when available data is found or by leveraging expert intuition, particularly in cases where experts possess deep knowledge of the organization's environment. Lastly, DR9 which focus is to develop a DM tool which is *aligned with mission/vision* of the organization, is ensured by the careful selection of data, especially KPIs that accurately represent the organization's core activities. The importance of *DR3 quality data*, serves as a crucial preliminary step for the data analysis phase. Next, the *DR7 output stability* is attainable thanks to the data analysis component.

As demonstrated in the literature review, data analysis consistently yields the same results, ensuring stability and consistency when the analysis is repeated. In contrast, *DR8 interpretability/comprehensibility* is addressed by intuitive analysis, as it helps make sense of the data in a way that is understandable to humans. *DR4 isolate key information* is fulfilled after the analyses (both data and intuition) by setting a threshold of information to be displayed in the final DM tool. In our case study, the threshold was set for the DEMATEL study to only show the 14 most important links while the data analysis has shown 20 resulting links. These thresholds are important to keep the most relevant information without overloading the DM tool and making it impossible or difficult to use. Furthermore, *DR10 integrating both data and intuition* is facilitated by the last phase of our artifact, which includes a structured process for resolving tensions that may arise between these two types of analysis. Then, *DR5 rapidity/real time* is achieved through both (almost automated) data analysis and (fast thinking) intuition analyses, along with a straightforward, transparent, and rapid integration process. Lastly, our ability to establish *DR6 interoperability* in this case is challenging and cannot be validated. In conclusion, it can be said that our DII framework meets nearly all of the design requirements provided by the decision-makers.

We rigorously assess the efficacy of our DII framework by comparing it to two broad categories of solutions: existing data-driven solutions and existing intuition-driven solutions. This comparative analysis is grounded in our set of 10 design requirements, which serve as the benchmark for evaluating each approach. By juxtaposing our framework against these established paradigms, we aim to determine in which scenario our DII framework represents a improved artifact.

We see in Table 4.5 that our DII framework outperforms both the existing solutions, based on the literature review, in data analysis and in intuition in at least 9 out of the 10 DR defined in Section 4.4. Only the interoperability criteria is not possible to validate in this specific settings. We thus demonstrate that our artifact is indeed an improved solution and consider it as a contribution as defined by Gregor and Hevner (2013).

Design requirements	Existing data-driven solutions*	Existing intuition-driven solutions*	Proposed DII Framework
DR1: Inclusion of intangible measures	✗	✓	✓
DR2: Inclusion of external data	✓	(✗)	✓
DR3: Quality data	(✓)	(✗)	✓
DR4: Isolate key information	✓	✓	✓
DR5: Rapidity/Real-time	✓	✗	✓
DR6: Interoperability	(✓)	(✗)	(✓)
DR7: Output stability	✓	✗	✓
DR8: Interpretability/ Comprehensibility	(✗)	✓	✓
DR9: Aligned with mission/vision	✗	(✓)	✓
DR10: Integrating both data and intuition	✗	✗	✓

**According to the literature review*

Table 4.5: Evaluation of DR of the DII Framework

4.8 Discussion

4.8.1 Theoretical contributions

Our initial research objective, which aimed to identify the prerequisites for developing a functional, current, and adaptable DM tool for managers, has been achieved through the use of semi-structured qualitative interviews with industry experts. The ten identified requirements have a general applicability across various industries and represent a valuable addition to the existing literature, serving as a foundational framework for the creation of DM tools.

Another theoretical contribution within this article is shown in Table 4.5 where we demonstrate that our DII framework outperforms the existing solutions present in the literature, thereby enhancing the current state-of-the-art in the field of DM. Our DII framework can thus be considered as contributions to the knowledge base as planned by the DSR.

4.8.2 Practical contributions

In the context of the *visual solution*, our DII framework findings clearly underscore the imperative of incorporating hybridity into the design of a DM tool. The scarcity of links that align with both empirical data and expert intuition (in bold in Figure 4.12) underscores the need for an integrated DM tool that effectively combines these two sources of insight, and reinforce our claim that these are to be seen as complementary rather than opposed. Figure 4.12 specifically emphasizes two areas that found their way into the tool either due to data analysis (depicted in green) or intuition analysis (depicted in blue). Some relationships proved impractical to quantify through data analysis, as the available data failed to meet the necessary methodological prerequisites for its application. In such instances, the financial perspective would not have been integrated into the tool were it not for the utilization of intuition analysis. Conversely, the learning and growth perspective is present in the tool solely by virtue of the results derived from data analysis. Indeed, none of the skeyes experts identified a connection between the KPIs within that lower perspective and other KPIs. The integration of the outcomes from these two analysis approaches has yielded a richer and more comprehensive DM tool, enabling the representation of the entire strategic landscape of the organization.

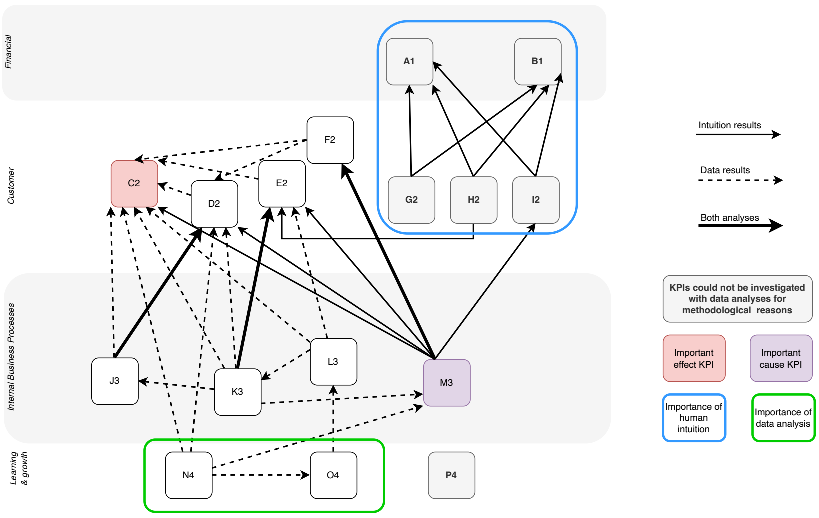

Figure 4.12: Visual result with highlighted discussion points

The enrich analysis depicted in Figure 4.12 also facilitates the organization's decision-maker in identifying crucial information, the KPIs that wield the most significant influence on the entire business landscape. In our example, the KPI labeled as 'M3' (shown in purple) emerges as a highly influential causal KPI, given its capacity to affect five other organizational indicators. This holds substantial managerial implications, necessitating careful consideration when incorporating this KPI into DM processes. Conversely, the red 'C2' indicator in the Figure assumes a vital role as an effect indicator, as it is impacted by changes in eight other indicators, providing valuable insights into the interconnectedness of various aspects of the organization's performance.

Figure 4.12 additionally illustrates that the indicator labeled as 'P4', regarded as a KPI by the organization, is not related with any other indicators. Its classification as a *key* indicator implies that it maintains significance for the organization, even as a standalone KPI.

4.8.3 Limitations

This study holds limitations which pave the way for further research directions. To begin with, there is room for improvement in the data collection process for identifying design requirements. We primarily relied on qualitative interviews with managers from diverse industries. However, this methodology is primarily exploratory, and as a result, the ensuing list of design requirements may be incomplete or inaccurate. A further research would involve conducting a large-scale validation study focused on requirements to design hybrid DM tools.

Additionally, we theoretically assume that the combination of data and intuition, or hybridity, leads to the development of superior DM tools, enabling the discovery of more insights than a standalone analysis. However, this assertion lacks empirical confirmation. A comprehensive study should complement this assumption by evaluating the relationship between hybrid DM tools and various factors, such as (i) organizational performance, (ii) tool adoption rates, or (iii) DM time, among others. Moreover, the extreme scenarios must be analyzed: How to manage the experts disagreeing with all hard data conclusions? would there be a need to discuss the outputs which yield the same conclusion or accept them as the truth ? How often should the outputs be challenged/updated? What is the ideal number of experts that should be included in the integration phase?

4.9 Conclusion

In this Chapter, our primary objective has been to design an artifact that seamlessly integrates both data and intuition into a DM tool. We firmly assert that these two sources of knowledge and analysis are not mutually exclusive but rather complementary, and we have identified a gap in existing solutions that fail to embrace this hybridity and address the potential tensions that may arise between them. To achieve this objective, we applied a rigorous Design Science Research Methodology, resulting in the creation and evaluation of our Data-Intuition Integration (DII) framework.

Our research not only fills gaps in the literature but also addresses practical needs by introducing novel design propositions. These contributions pave the way for the development of DM tools that incorporate both data analysis and intuition, resulting in more robust and trustworthy solutions. The real-life scenario demonstration and evaluation of our DII framework confirm its ability to harness the added value of both data and intuition, ultimately providing an enhanced solution, guided by the 10 design requirements we have carefully considered.

4.10 Appendices of Chapter 4

Appendix 1 – Descriptive tables of the respondents for the design objectives elicitation

ID	Gender	Job title	Industry	Size	Type
a	Male	Chief Strategy and Development Officer	Telecommunications	Large	Private
b	Male	Chief Financial Officer	Roofing, cladding, insulation	Middle	Private
c	Male	Managing Director	Software	Large	Private
d	Male	Co-founder & CEO	Publishing house	Small	Private
e	Male	Managing Director	Sustainable development	Middle	Public
f	Male	Operations Director	Consultancy Marketing	Small	Private
g	Female	Head of Cross Strategies Unit	Utilities	Large	Public
h	Male	Operations Director	Home appliance	Middle	Private
i	Female	Expert in Management and organizational control, Risk Officer	Federal public services	Large	Public
j	Male	Regional Managing Director	Paper and cardboard packaging	Middle	Private

Table 4.6: Descriptive information of the sample

Appendix 2 – Interviews extracts justifying the design requirements presented (DR)

Design requirements	Interviews extracts
DR1: Inclusion of intangible measures	*"A trend that I have observed over probably the last three years is that there are more and more elements other than financial ones that are added to decision-making [...] softer elements , HR type, diversity inclusion, that sort of things."*, Respondent a. "*There is still a dimension, [...] it is the importance of CSR, of all this data which can come from the environment, from the well-being of the people who contribute to the environment, I believe that they are still underestimated [...] in my opinion, decision-making should not be based solely on the accounting, quantitative, objective data that comes to us regularly but must also be influenced as much by a set of data that is much more difficult to perceive and quantify.*", Respondent b. "*[The organization] has to be very flexible and the human factor becomes something very important and therefore there in a small company there is a reactivity based on certain parameters which are not necessarily tangible.*", Respondent c. "*There is a part of the data that is measurable and a part of the data that is less measurable and is more derived from discussions, etc. So there are quite a few different types of data.*", Respondent f.
DR2: Inclusion of external data	"*So we obviously have a lot of internal data and then we have access to some external data. [...] Some slightly more local analyzes which give us a little more idea of the market opportunity, of our position in the market and then obviously we have a mass of internal data, more and more. [...] the forecast at [organization name] is more powerful now with AI and machine learning than before, it's because we've opened up to external data: the weather, exchange rates , geopolitical tensions, Twitter hashtags, all data and information that we didn't use before.*", Respondent c. "*We use a lot of data regarding the situation and the evolution of the situation over time at different levels. Clearly, these are important data. We also inevitably take into account external data such as market trends and feedback from our clients.*", Respondent f.

DR3: Ensuring quality data	"*I know what the problem is with us, the problem is the quality of the data. [...] It's fine to want to rely heavily on purely data, but there are really good quality data, it's extremely difficult, extremely difficult! And even if you have quality employees [...] there is nothing to do, what there is in the system is still always linked to inputs made at a time when the other is good we all know the adage "garbage in, garbage out" so if these inputs are not resolved in a qualitative way.*", Respondent c.
DR4: Isolate key information	"*Succeeding in isolating the real key drivers of our business. That's really it, that's success, because there are hundreds of drivers and we can quickly get lost in a lot of things and model endless chaos. For me, it's more about really focusing on okay there are really 5 to 10 key drivers of our business and personally, I'm in everything that is planning and I'm much more of a macro trend enthusiast than detailed modeling, scenarios, and stuff. So it's really: we have these 5 to 10 key drivers and we really spend quality time imagining how macro trends will impact these 5 to 10 key drivers.*", Respondent a. "*We have a ton of data, but what's important is being able to extract what's most relevant. Well, the more important the data is, the more potentially rich it is, but also the more complicated it is to extract meaningful data versus meaningless data. And as I was saying, it's a bit the same thing we do for analytics. We can't say that the more data we have, the more information we have. The more data we have, the more potentially interesting sources we have on which we can possibly build information, but that's it. So, it requires even more work to try to extract what really makes sense.*", Respondent f. "*We still have work to do, but we are making progress, and it's about agreeing on the indicators, what are the key indicators we need, whether we often end up with too many indicators in the end.*", Respondent g. "*We can't track hundreds of indicators on a monthly basis, but indeed, when creating a scorecard, we need to identify the 10 to 20 key indicators, and for those, we really need to allocate the resources to track them correctly because there's no room for error [...] In a strategic or operational plan, you need to prioritize. [...] If there are too many, it becomes unreadable, and people get discouraged, and they'll say, 'No, we're not going to track all of this anymore.*", Respondent i.

	"*Too much data overwhelms, so today we have more rather than less, and we can no longer digest all the information we have. So, it's the role of the leader to be clear about the fundamental indicators.*", Respondent j.
DR5: Rapidity/Real-time	"*The first thing that comes to mind [when we talk about decision-making] is the difficulty of making decisions quickly enough. This is a recurring subject, and we are all aware that a bad decision is better than no decision because it allows us to channel resources. Not making a decision means that resources continue to be spent on various things. At least with a bad decision, we have decided to allocate resources to one thing over another, and it may turn out to be the right thing to do in the end.*", Respondent a. "*The industry is moving very, very fast, the competition is constantly moving, and customer expectations are changing rapidly.*", Respondent c. "*The speed of access to information, that's clear... that's what interests me. I need a tool that is much faster because in my sector, I cannot afford to wait too long before making a decision. I feel that the risk I am taking by waiting is greater than the risk I would take if I waited to have all the information that would allow me to make a more objective decision.*", Respondent e. "*What we need, and increasingly so, is first, the speed of having access to information. Not all business processes have evolved to real-time operations. We can't assume that today we consistently have the information we need in real-time; there's often a delay of several days or weeks due to month-end closings and IT update schedules... So, the more instantaneous the information, the more agile we can be in how we manage things, and this will certainly help [...] the faster we can access things, the more it will help us make good decisions at the right time.*", Respondent h.
DR6: Interoperability/Compatibility	"*In the negative side, there is the proliferation of tools that's a big challenge. Everyone comes up with a brilliant idea "oh, let's create a new monitoring tool and I have a great idea" then you have an app but your app is not compatible with the app that was developed in another country and then you end up with too much data so there's a need for rationalization.*", Respondent e.

	"*So obviously new technologies make our lives a lot easier because we save an incredible amount of time when it comes to reporting. Before, we asked people to send their indicators and they do so in formats where everyone has their own table format and then we have to put everything back in order. Rather than sending each other Excel files where we no longer know if it's the right version, if it's the version that has been validated by everyone.*", Respondent g.
DR7: Output stability	"*I find that you can't tell people one day that 'this' is super important to do, and then the next day tell them, 'No, I don't think so at all,' you know. So yes, it's unstable and therefore uncomfortable for the employees.*", Respondent g.
DR8: Interpretability/ Comprehensibility	"*There are certain indicators where it's relatively simple because there are clear definitions, you know exactly what's behind them. But that's not always the case, and so what's complicated is that we always wonder what these indicators will be used for [...] ideally, they should be documented and justified so that the continuity and stability of the indicators and the interpretation we'll make of them can be ensured.*", Respondent g. "*People need to understand. If people don't understand, it's pointless. You can create all the complicated formulas you want, even if they are correct, they won't yield anything...*", Respondent j.
DR9: Aligned with mission/vision	"*In my opinion, a strategic map is composed of the priority axes that will be used and developed in order to achieve the company's mission and vision. The company has a vision, it has a mission, and [it's essential to know] which are the axes, which are the levers that will be used to address this mission and vision.*", Respondent b.
DR10: Integrating both data and intuition	"*I believe that a mix of both, you know, is simply necessary. Now, whether one should give greater weight to one over the other, honestly, I don't know. But I think a company that relies solely on rational models, in my opinion, is not optimal. Conversely, if one only relies on intuitive models, that's not optimal either. I believe there needs to be a certain form of hybridity.*", Respondent b. "*When we provide the data, the insights, and mix it with personal experience, that's when we really see leaps in efficiency.*", Respondent c. "*I have a very Anglo-Saxon mindset, which means I strongly believe in indicators. I believe even more that we should especially make room for intuition as well.*", Respondent d.

"*In my sector, I believe it's important to have a good mix between intuition and information validated by management. [...] That's what I also expect from information systems, to determine the drivers influencing our efficiency, including those we might not have initially considered, and to learn from this in order to focus management on the right things. For me, the advantage of having an objective tool with these indicators is that it allows us to either support or contradict our intuition. However, I think the 'gut feeling,' at least in my leadership philosophy, is very important. [My organization] rely solely on reports to make decisions, so they wait for information, which is not presented synthetically through BSC but rather in the form of administrative reports. In contrast, in Agile management, I believe there are moments when decisions must be made based on a gut feeling, substantiated by some results, even if all the results aren't available yet. What's most interesting is to determine, especially when we make a wrong decision, whether the information obtained from a system, as you describe it, helps to confirm whether we made the right decision or not. Because the system might have shown the same thing, and we might have made the decision anyway, or perhaps not. So, that's what interests me in management tools.*", Respondent e.

"*So, the advantage, in any case, of incorporating intuition into the decision-making process, as I prefer it, would be to take into account, of course, one's experience and all these elements that are not always measurable or quantifiable. There are indeed many such factors that should be considered. So, I think about that... Yes, I believe that both [intuition and data] are complementary, and to gather the most input for making the best decision, I think both are necessary. Data, perhaps, could be an interesting starting point, for example, but it should then be validated through fact-checking. This could certainly serve as a good foundation that needs to be supplemented. If there's a discrepancy between intuition and what is observed, it would warrant careful consideration. This could involve reassessing one's intuition or potentially identifying errors in the data or other factors. In any case, it would warrant reflection*", Respondent f.

"*The ideal solution would be a combination of both. That is, someone who has a deep understanding of the business, extensive experience within the organization over time, along with objective indicators rather than relying solely on intuition.*", Respondent i.

"*I am a strong advocate for reconciling intuition and theory, for being able to apply a theory to intuitions, to model intuitions in some way.*", Respondent j.

Table 4.7: Interviews extracts justifying the design requirements (DR)

Part III – Conclusion

General Conclusion

In this general conclusion, we synthesize the key findings and contributions of the four studies presented in the previous Chapters. We also discuss the challenges that this research faces and propose some further research directions.

Summary of the findings

This thesis dissertation objective is introduce an innovative approach that combines empirical data and human expertise, providing theoretical insights and methodological recommendations, to enhance the current knowledge in the field of strategic and performance management. Four studies have addressed complementary research questions to obtain a better understanding on the integration of empirical data and organizational experts knowledge in the SM. Table 4.8 summarizes these four Chapters and depicts each study's related research question, method and provide key findings.

The findings of this dissertation make a substantial contribution to the scientific literature beyond the field of strategy maps. By addressing the intersection of strategic management, sustainability, and data analytics, this thesis makes notable contributions to the broader management literature. The following discussion highlights three key contributions: the reinforcement of holistic management view, the advocacy for cross-domain exchanges in methodologies, and the promotion of the incorporation of sustainability in strategic DM.

First, this thesis makes a key contribution by highlighting the importance of taking a comprehensive approach to effective management. In the past, management literature tended to focus solely on either quantitative metrics or qualitative insights. However, this thesis, through its examination of hybrid strategy maps, underscores the value of combining numerical metrics and qualitative insights. It argues that concentrating too narrowly on either quantitative or qualitative aspects can result in incomplete decision-making and strategic management. This emphasis on holistic management principles significantly adds to the ongoing con-

chapter	Research question(s)	Method(s)	Key findings
Chapter 1: Unveiling the Landscape of Strategy Maps	• "How did the literature about Strategy Maps design evolve over the past two decades?" • "What are the trends in terms of methods and methodology types for Strategy Maps design?" • "What are the trends in terms of data sources for Strategy Maps design?"	Systematic Literature Review	• SMs have been increasingly studied in the literature since the creation of the tool. • SMs are mostly constructed using soft data and qualitative methods. • Very few investigations have proposed to build SMs using hard data.
Chapter 2: Navigating Data-Driven Horizons	• "How to integrate factual data in the design of Strategy Maps?"	Quantitative framework	• Proposition of a data-driven framework to build SMs
Chapter 3: Connecting Strategy and Sustainability	• "What are the comparative strengths and challenges associated with the different architectures in the construction of a sustainable Balanced Scorecard?" • "What are the comparative strengths and challenges associated with the different architectures in the use of a sustainable Balanced Scorecard for DM purposes?" • "What are the most recommended and discouraged application cases for each type of sustainable Balanced Scorecard architecture?"	Qualitative interviews and focus groups	• Highlighting the advantages and difficulties of building sustainable SMs • Highlighting the advantages and difficulties of using sustainable SMs for DM • Identification of the appropriate and not recommended application scenarios
Chapter 4: Finding Common Ground Through a Hybrid Approach	• "How can an organization integrate its human expertise and factual data to build more valid and robust SMs?"	Design Science Research	• Proposition of a hybrid methodology to build SMs based on data and human expertise

Table 4.8: Summary of the four studies

versation in management literature, encouraging a more integrated and balanced viewpoint.

A second contribution of this dissertation comes from highlighting the importance of exchanging methodologies across different domains. The use of vector-autoregression models and Granger causality tests, borrowed from a different scientific field, demonstrates the advantages of drawing on methodologies from diverse disciplines. This cross-disciplinary approach pushes against the traditional limits of strategy and management literature, prompting scholars to delve into and incorporate insights from related fields. By infusing ideas from another scientific domain, the thesis enhances existing literature with innovative methodologies that may not have been typically linked to strategic management.

Finally, this thesis looks into how businesses can adopt sustainability by incorporating measures for sustainability, environmental evaluations, and social responsibility directly into their strategy maps. It serves as a practical guide and shows that it's possible for organizations to align their strategies with environmental and social objectives. In a world where businesses are closely examined for their impact on the planet and society, my thesis provides a practical approach to this research domain.

Contributions

Collectively the four Chapters included in this dissertation provide new insights on building robust, validated strategic DM tools. These insights bring several theoretical, methodological, and managerial contributions.

Theoretical contributions

Chapter 1 provides theoretical contributions in two specific ways. First, while a systematic literature review doesn't generate new data or empirical findings, it does contribute to the theoretical body of knowledge by synthesizing and organizing existing research. In this case, while the SM tool has been around for more than two decades, no previous work did provide a summary of the methodologies, data source and applications of the tool. Second, Chapter 1 allows to highlight gaps in the current state-of-the-art such as the lack of hard data, quantitative methods to build the SM. This outcome contributes to the literature by providing a foundation for further research.

Chapter 2 enhances prior literature by extending the research of Bukh and Malmi (2005). It addresses their criticism regarding the absence of validation for the causal relationships within the tool, and it applies the Granger methodology proposed by them to construct and validate the causal links of the SM among the organizational KPIs.

Chapter 3 contributes to existing research by exploring further the comparison of sustainable SMs, advancing the prior work of Hansen and Schaltegger (2016) by providing insights on the comparison between the construction and use of SBSCs.

Chapter 4 brings theoretical contributions to the field of DM tools. First, we achieved our goal of identifying key requirements for creating effective DM tools through interviews with industry experts. These ten requirements can be applied widely across industries and form a solid foundation for future tools. In addition, our Chapter demonstrates that our framework outperforms existing solutions, extending prior work in DM.

Methodological contributions

Chapter 2 provides with a methodological contribution by introducing a new data-driven framework for creating SMs. This framework is a first of its kind in the context of SMs. It offers a practical framework that organizations and researchers can use to build more accurate and effective SMs. By relying on data, this approach ensures that causal relationships within the KPIs of these maps are based on solid evidence. In essence, this innovative method improves the usefulness of SMs in strategic DM and performance management.

Similarly, Chapter 4 not only extends the current body of research but also enriches the literature by proposing the very first attempt to integrate human expertise and data analytics in the development of causal strategic DM tools. The resulting framework in this Chapter is designed independently of the SM tool, making it adaptable for use with any strategic DM tool. This reusable approach contributes to the existing literature in this field.

Managerial contributions

Practitioners can benefits from our research outputs in many ways. Chapter 1 offers them a comprehensive overview of the methodological possibilities to build their own SM. Chapter 2 and Chapter 4 both provide with methodological framework to build either a data-driven SM or a hybrid SM. Lastly, if they are interested in sustainable strategic management, Chapter 3 offers a guide to choose the appropriate sustainable SM for their specific context.

Challenges

The research outputs of this thesis are intricately connected to a multitude of challenges, which were not directly considered in the previous Chapters but are discussed hereafter.

Technology acceptance and corporate culture

While numerous companies have effectively embraced cutting-edge technologies, including artificial intelligence, the Internet of Things, robotics, and virtual reality, there remains progress to be made for other organizations. These organizations are not yet adequately equipped, be it in terms of financial resources, knowledge, or readiness, to fully leverage the latest technological innovations. Overcoming the skepticism some companies hold regarding the integration of data and mathematical/statistical models for critical strategic DM may present a significant challenge in practically applying the outcomes of our research.

Data quality

Data quality is about how accurate, consistent, complete, and reliable data is. It concerns making sure no mistakes or problems appear in the data, so it can be trusted and used effectively. Good data quality is important for making smart decisions, doing useful analyses, and keeping data-driven processes and tools working well. Data quality is vital for data-driven and hybrid DM tools. It is the foundation these tools are built upon, directly affecting how precise, reliable, and effective their results are. The adage "*garbage in, garbage out*" stresses how important it is to have good data as input because it greatly influences the quality of the insights and decisions these tools provide. While we did not dig into this concept theoretically in this dissertation, it remains truly important in practice. Future research might take a closer look at data quality as it plays a consequent role in how well data-driven and hybrid DM tools work.

(Over) Trust in data and in KPIs

Quite related with the challenge discussed above, relying too heavily on data and KPIs to make decisions in a company can pose significant risks and challenges. While data provides valuable insights, it may not always capture the full complexity of a situation. Overemphasis on quantitative metrics can lead to a narrow perspective, overlooking qualitative aspects and the human element. Inaccurate or incomplete data can also misguide decisions, potentially resulting in poor outcomes. Moreover, an over-reliance on historical data might hinder adaptability in rapidly changing environments. Additionally, the temptation to manipulate or selectively present data to support a particular narrative can compromise the integrity of DM processes. It is crucial for companies to strike a balance between data-driven insights and experts knowledge and intuition considerations, fostering a more holistic approach to DM that accounts for the nuances of real-world scenarios.

Data storage and security

Furthermore, this thesis did not explore the concepts of data storage and security, two critical aspects in the world of data management. Data storage covers the retention of data, ensuring it is organized and accessible for future use. Data security, on the other hand, can be seen as a shield, protecting data from unauthorized access or harm. While the importance of data storage and security is undeniable, it is crucial to acknowledge that this thesis dissertation did not examine this in a theoretical sense.

Environmental footprint and sustainability

The impact of organizations on the environment is a significant, current concern. While Chapter 3 of this thesis opens the focus of this dissertation towards sustainability, it is mainly centered around strategic sustainability and does not taken into account the practical impact of our solutions and frameworks on sustainability. It is essential to be attentive and make choices (both technical and technological) in line with a sustainable IT mindset. This is a challenge because it is becoming an increasingly scrutinized aspect by organizations, their customers, and governmental authorities who may implement strict measures in this regard.

Ethical concerns of data-driven DM

Making decisions based on data can present ethical concerns, particularly when relying on historical data that may carry biases. Historical data often reflects societal prejudices and systemic inequalities, potentially perpetuating unjust practices if used unquestioningly. For instance, if past decisions were influenced by biased factors, using that data to guide future decisions can inadvertently replicate and reinforce those biases. This can result in unfair treatment and discrimination, disadvantaging certain groups. It is essential for decision-makers to critically examine and address biases in the data, actively working to mitigate these ethical concerns. Additionally, incorporating diverse perspectives and ethical considerations into the DM process helps ensure that data-driven decisions align with principles of fairness and justice. Ethical data use requires a commitment to transparency, accountability, and continuous scrutiny to avoid perpetuating historical inequities.

Limitations and further research directions

On KPIs selection

Intrinsically, there are no good or bad KPI to include or exclude from the SM, whether it is data-driven, intuition-driven or hybrid. The relevance of the set of KPIs to include in the SM is determined by a combination of numerous factors including: the relevance of the KPI regarding the organization's strategy, the obligation to monitor the KPI by external stakeholders, the total number of KPIs acceptable or desirable in the model, the redundancy of information between KPIs, the trust from the stakeholders and decision-makers towards the KPI, and many more.

In Chapter 2, we have set some convenient boundaries to accept a KPI in the data-driven framework. The data-driven approach requires that the KPIs follow some specific characteristics in order to be statistically valid. We decided to look at the data availability and quality (no missing data, good quality, long time period) and relevance of the KPIs (no high correlations between two KPIs). A number of other selection criteria could have been applied here. For example, the 12 characteristics defined by (Eckerson, 2009) could have been explored as well.

To enhance the criteria for selecting KPIs in organizational analysis, a more research-based approach can be adopted. Drawing from existing literature on best practices for KPI selection, the research can delve into factors such as relevance, measurability, and alignment with organizational objectives. Consideration should be given to the *SMART* criteria (Specific, Measurable, Achievable, Relevant, and Time-bound) to ensure that selected KPIs are well-defined and contribute meaningfully to organizational success. Moreover, the research can examine the need for a balanced KPI set, incorporating both quantitative and qualitative measures to provide a comprehensive view of organizational performance. Inclusiveness and collaboration in the KPI selection process, involving stakeholders from different levels of the organization, can ensure that diverse perspectives are considered. Lastly, a continuous review and adaptation of KPIs in response to changing organizational dynamics and industry benchmarks should be emphasized to maintain the relevance and effectiveness of the performance measurement framework.

On visualization

As mentioned in the background Chapter, we tried to stick to the original BSC and SM visuals, as developed by the two authors. We initially chose to use a well-known tool such as the BSC as a starting point for our visual representation. The BSC provides a structured framework with its four perspectives—financial, customer, internal processes, and learning and growth. This has brought advantages such as the savings of downward links analysis or a cleaner visual. However, we recognize that not all organizations may be familiar with the BSC, and some may not have the desire to align strictly with these four perspectives.

Technically and methodologically, we could open the visual representation outside the confines of the BSC tool and make our approach more accessible to a broader range of organizations, i.e. organizations with no prior knowledge of the BSC or those who may not find it suitable to fit within the specific boundaries of the four traditional perspectives. Exploring alternative visual frameworks beyond the BSC/SM may be a subject for further research.

On the generalizability of the results

In this dissertation, we have taken one recurrent case study example throughout the different Chapters. We firmly believe that this collaborator, skeyes, is a relevant organization for the demonstration and application of our designed artifact. Indeed, skeyes had numerous concerns regarding the side effects of their indicators during DM or when an external force has an impact on one or more KPIs. The managers were eager to understand the cause-and-effect relationships that exist among their KPIs but this organization collects an incredibly large amount of data and KPIs, making it quite challenging to intuitively comprehend the interrelations between the KPIs. The development of the artifact and its application to their data marks a significant initial step in their performance control process. However, skeyes does not represent all types of organizations. Indeed, it is an organization with a monopoly in Belgium, an autonomous public authority entity with many external influences (geopolitical, environmental, etc.). The fact that the organization is governed by these characteristics may raise questions about the generalizability of our results. Even though the artifacts developed in various design cycles were conceived in an agnostic manner towards skeyes, it remains that the practical environment of our DSR methodology has been strongly influenced by this organization.

Additionally, it appears that our artifact is intended for businesses that are mature in terms of data collection, analysis, and culture, as well as mature in terms of strategic thinking. One way to make our artifacts accessible to less data-mature businesses is possible in two ways: (i) opting for simpler quantitative methodologies than those used in our examples and (ii) relying more on the intuition and knowledge of experts. The hybridity here may not be balanced between soft and hard data, but their combination could still yield interesting results for businesses.

Exploring the generalizability of our results through additional research would be valuable. Conducting various case studies across different types of organizations and at different levels of data maturity could provide insights into the broader applicability of our findings. By examining a diverse range of scenarios, we can enhance our understanding of how our methods and artifacts may be adapted to suit a variety of contexts. This approach would contribute to the robustness of our conclusions and better inform organizations about the potential benefits and challenges of implementing our strategies.

On the inclusion of broader strategic steps

In each of the Chapters that make up this thesis, we have chosen to skip the preliminary steps leading to the practical construction of the BSC or the SM. Indeed, designing a BSC/SM is part of a broader process that also includes defining the vision and mission of the organization, in addition to steps like choosing indicators, estimating causal relationships, and validating causality. We intentionally set aside these initial stages while developing the artifact because they are specific to each organization and have limited generalizability.

In a pragmatic sense, we do not anticipate modifications to the steps outlined in the framework developed and presented as an artifact. The definition of the company's mission and vision, as well as the transformation of these into strategic objectives, should probably be introduced as additional steps at the beginning of the artifact.

Further research should delve into the seamless integration of the additional steps, such as defining the company's mission and vision and translating them into strategic objectives, with the existing steps of the artifact. Understanding how to undertake these new components in a coherent and harmonious manner within the established framework is essential. This exploration will contribute to refining the practical application of the artifact, ensuring a comprehensive and well-aligned process for organizations seeking to develop their BSC or SM. By investigating these additional steps, researchers can provide valuable insights to guide organizations in creating a more holistic and effective strategic management tool.

On the scalability of our artifact

Scalability is an important issue for our designed artifact. It is important because it lets a system grow smoothly as data increases. It ensures that the system performs consistently well, even during high demand. Scalability also allows for easy adaptation to changes and new features without major disruptions. It helps future-proof the system, making it capable of staying relevant as technology and needs evolve. In a global setting, scalability is crucial for reaching different organizations, adapting to various application contexts, and meeting specific needs effectively.

It has been relatively easy to increase the scalability of our hard-data analysis part. Indeed, the designed artifact in Chapter 2 was not very scalable as many steps of the data analysis were still manually carried out. The analysis, running on a code, has been made (semi) automated for Chapter 3 and Chapter 4, allowing to have a large number of input KPIs. This explains why the steps of verification of correlation coefficients and OLS regressions presented in the artifact of Chapter 2 are no longer included in the artifacts of Chapters 3 and 4. The automation allows for: a shorten proceeding time, including a larger sample of KPIs, the possibility to add new dimensions in the BSC/SM, and less manual errors.

On the contrary, the expert intuition analysis is difficultly scalable, endangering the scalability of our whole artifact. Indeed, it is challenging to save time when adding numerous KPIs for analysis by organizational experts. The cognitive load and time required make scalability highly unlikely. One approach to enhance scalability from the experts' intuition perspective would be to subdivide the KPIs into different domains and have experts analyze only the KPIs within their specific domain. However, this implies a greater number of experts, and it is likely that some inter-domain causalities may not be revealed in the analyses.

Further research could explore alternative strategies for improving scalability in the analysis of numerous KPIs, considering potential trade-offs between sub-dividing KPIs into domains for expert analysis and the risk of overlooking inter-domain causal relationships.

Scientific work portfolio

The PhD thesis draws upon a multitude of scientific publications that are listed below:

Thesis articles

1. (Published) **Pirnay, L.** & Burnay, C. (2021, June). *Data-Driven Strategy Maps: A Hybrid Approach to Strategic and Performance Management Combining Hard Data and Experts' Knowledge.* In Proceedings of the Doctoral Consortium Papers Presented at the 33rd International Conference on Advanced Information Systems Engineering (CAiSE'21). (**Partially in thesis introduction**)

2. (Finished) **Pirnay, L.**, & Burnay, C. (TBD) *Rise of Data Analytics: Towards a New Era for Strategy Map Design? A Systematic Literature Review.*Full-length paper currently submitted to the International Journal of Productivity and Performance Management. (**Chapter 1**)

3. (Published) **Pirnay, L.**, & Burnay, C. (2022). *How to build data-driven Strategy Maps? A methodological framework proposition.* Data & Knowledge Engineering, 139, 102019. (**Chapter 2**)

4. (Published) **Pirnay, L.**, & Burnay, C. (2021, May). *Data-Driven Causalities for Strategy Maps.* In International Conference on Research Challenges in Information Science. Springer, Cham, pp. 409–417. (**Partially in Chapter 2**)

5. (Finished) **Pirnay, L.**, Clement, A. and Burnay, C. (TBD) *Building Green Strategies: An Empirical Comparison of Sustainable Balanced Scorecards Architectures.* Full-length paper currently submitted to the Journal of Cleaner Production. (**Chapter 3**)

6. (Finished) **Pirnay, L.**, & Burnay, C. (TBD) *From 'Data vs Intuition' to 'Data ft Intuition' – A Framework to Design Hybrid Decision-Making Tools.* (**Chapter 4**)

Additional work

In addition to the scientific publications directly linked to the topic of the thesis, various other research projects have been undertaken during the PhD. These projects have provided opportunities for collaboration with other researchers and institutions, facilitating the sharing of knowledge and ideas. Overall, the additional work accomplished during the doctorate has enriched the research experience and has contributed to the overall quality of the thesis.

1. (Published) **Pirnay, L.**, Deventer, C., and Amaral de Sousa, V. (2023) *Providing Customer Value through Non-Fungible Tokens: A Preliminary Study.* Published in The 56th Hawaii International Conference on System Sciences (HICSS56).

   This paper discusses the growing popularity of Non-Fungible Tokens (NFTs), which are digital certificates of ownership that can be linked to virtual or physical assets. NFTs have gained significant traction, especially in the context of metaverses, online shared virtual spaces. Many organizations are launching NFT initiatives for various purposes such as customer retention, generating new revenue streams, and showcasing technological prowess. The paper focuses on understanding how organizations provide value to NFT users based on the unique characteristics of these tokens. To accomplish this, the authors conduct a preliminary study analyzing 46 NFT initiatives from 42 different companies. The ultimate objective is to lay the groundwork for future research on the values associated with NFTs and to aid in the development of Information Systems tailored for NFTs.

2. (Published) Deventer, C., Amaral de Sousa, V. and **Pirnay, L.** (2024) *NFTByBrands: A Proposed-Value Framework for Analysis and Design of NFT Initiatives.* Full-length paper currently under review in the International Journal of Electronic Commerce.

This paper is an extension of the previous NFT paper, it introduces the NFTByBrands framework, which addresses the growing popularity of Non-Fungible Tokens (NFTs) in the context of the metaverse and how brands can strategically utilize them. NFTs serve as digital certificates of ownership for virtual or physical assets and have gained traction among brands seeking to retain customers, create new revenue streams, or showcase their technological prowess. While NFTs have primarily been associated with financial returns, this paper argues that they can offer various forms of value to their target audience beyond just monetary gains. The NFT-ByBrands framework is developed based on the concept of customer perceived value and is informed by an analysis of 50 NFT initiatives launched by 42 different brands. This framework aims to help brands identify the diverse types of value they can deliver through their NFT initiatives, offering a structured approach to ensure the success of these ventures. Additionally, the paper suggests that this framework can serve as a foundation for further research into the value of NFTs and proposes a research agenda to explore this evolving field. Ultimately, the NFTByBrands framework provides valuable guidance for brands looking to leverage NFTs effectively in the evolving digital landscape.

3. (Finished) Lega, M., Giunta, B., **Pirnay, L.**, Simonofski, A. and Burnay, C. (TBD) *Avoiding information overload in e-participation: a data-driven prioritization framework for policy-makers.* Full-length paper currently under review in IJIM Data Insights.

This paper addresses the challenge faced by policy-makers in handling the abundance of citizen opinions collected through e-participation platforms, often leading to information overload. To mitigate this issue, the paper introduces a prioritization framework for citizens' proposals, rooted in Design Science Research (DSR). The framework is tested in collaboration with the European Commission, offering three main contributions. Firstly, it establishes theoretical criteria for prioritizing proposals, focusing on popularity *and polarization. Secondly, it presents automated and quantitative metrics to evaluate these criteria objectively. Lastly, it offers a prioritization matrix that enables policy-makers to visually assess the relative importance of citizens' proposals. This innovative framework aims to alleviate cognitive overload in e-participation analytics by providing a systematic method for quantitatively prioritizing citizens' ideas, aiding policy-makers in their decision-making processes.*

4. (Working paper) **Pirnay, L.**, Mazuin, C., and Burnay, C. (TBD) *One Dashboard Does Not Fit All: Exploration of the Relationship Between Dashboard Visual Features and End-User Characteristics.*

This paper addresses the issue of designing effective dashboards in organizations operating in complex and uncertain environments. Organizations often rely on supporting systems like Business Intelligence to aid decision-making, and dashboards are a common tool that provides visual representations of data for users to quickly comprehend and interact with information. Dashboards consist of both functional features like drill-down and filtering, and non-functional features like layout and display, which can significantly impact dashboard adoption. However, generic guidelines for non-functional dashboard design are difficult to establish due to their subjectivity. To address this gap in the scientific literature, the paper conducts a two-stage qualitative study involving interviews and observations. It examines preferences for different visual features based on end-user profiles, considering both personal and professional characteristics. The study confirms that the characteristics of a dashboard's user are crucial when designing non-functional dashboard features. As a result, the paper provides a set of profile-specific guidelines to assist designers in customizing dashboards to better suit their users. This research has implications for requirements engineering, technical design, and dashboard implementation within organizations, emphasizing the need for further research in this area.

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