Project portfolio management for AI projects

Developing a framework to manage the challenges with AI portfolios

Master's thesis in Management and Economics of Innovation

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Abstract

Artificial intelligence (AI) has rapidly developed during the past decades, opening the doors to new opportunities for many organizations. The automotive industry is no exception, and AI is regularly seen as a leading technology for many disruptive trends. Thus, successfully incorporating AI as a capability in the organization is essential for future competitive advantage and growth. However, many organizations still experience challenges reaping the fruits that scaled AI initiatives present. Some of the challenges for reaching enterprise-wide implementations of AI include the difficulty of selecting which initiatives to scale, and communicating the business value of these. Similar problems have previously been tackled within the research field of project portfolio management (PPM). Indeed, previous literature has a history of adapting PPM practices to suit the needs of new project types. However, the portfolio management literature on AI projects is seemingly non-existent up until this point. In collaboration with researchers and a newly established department at Volvo Cars, responsible for applying and diffusing AI in the organization, this study sets out to develop a new framework for the PPM practices of AI projects. To fulfill this aim, two research questions are investigated in this thesis. The first question delineates the main characteristics of AI projects from a portfolio perspective. The second research question explores how PPM practices need to be customized to support these characteristics. Regarding the first question, the study identifies significant characteristics relating to the portfolio evaluation criteria *Reward and cost, Risks,* and *Synergies*. In addition, AI projects exhibit characteristics such as heavy dependencies on data, experimentation-driven development, and high levels of unpredictability. Building on these findings, the second research question establishes that PPM practices for AI projects need to be customized accordingly. The findings point to the necessity of structured and ordered PPM practices, where projects are continuously evaluated as information is gathered. Therefore, techniques including scorecards and integrated exit criteria are proposed to reduce the projects and achieve a strategically aligned AI portfolio. In conclusion, to handle the unpredictable nature of AI projects, project selection tools from previous literature need to be customized. Furthermore, particular emphasis needs to be placed on the structure and order of the PPM to support information acquisition in a resource-efficient manner, even if AI projects often take an experimentation-driven approach to development. Ultimately, to successfully implement PPM practices for AI portfolios, adopting a perspective of *project reduction* rather than relying on previous notions of *project selection* seems essential.

Keywords: project portfolio management, project selection, artificial intelligence, AI, PPM

Contents

1. Introduction

Advances within artificial intelligence (AI) during the past decades have presented immense opportunities for organizations in the automotive industry. Not only does it enable new growth opportunities by transforming consumption of mobility, but it also presents opportunities for automating large parts of the manufacturing process (Breunig et al., 2017). Similarly, Kässer et al. (2018) recognizes AI as an essential technology for facilitating four major disruptive trends faced by the industry, including connectivity, electrification, autonomous driving, and shared mobility. Despite the opportunities for creating a competitive advantage, few organizations in the automotive industry manage to reap the fruits AI presents. Capgemini Research Institute found in a survey with 500 automotive executives that only 10% of the companies in the industry successfully implement AI at scale (Capgemini Research Institute, 2019). However, five times as many organizations are experimenting with proofs of concepts, pilot projects, or have chosen to implement AI only in isolated business units (Capgemini Research Institute, 2019). Although no silver bullet exists for reaching enterprise-wide AI diffusion, some identified problems provide a direction to where solutions could yield great impact. As cited by the executives, some of the most prominent hurdles include organizational challenges such as difficulties in selecting which AI initiatives to scale, and the challenges in demonstrating future financial returns during the pilot stage (Capgemini Research Institute, 2019).

In an effort to reach enterprise-wide diffusion of AI initiatives, the Volvo Car Corporation has recently organized a department responsible for diffusing AI throughout the organization. In the centralized team, similar problems as the ones outlined by Capgemini Research Institute have been encountered. Not only is the selection of which initiatives to pursue perceived as difficult, but the fact that AI projects in general are recognized as unpredictable render many previously established techniques unreliable. Additionally, the novelty of AI makes project classification and estimations uncertain. One possible solution for these problems, identified by the team, is the development of portfolio practices to suit the characteristics of AI projects. Indeed, solutions to similar problems associated with project selection have previously been researched within the field of project portfolio management (PPM) (Cooper et al., 2000). Hence, the search for refined PPM practices for AI could most probably be found by further investigating these issues from the perspective of AI.

1.1 Background

Project portfolio management finds its roots in the seminal works of Markowitz (1952), who formulated the groundwork for modern portfolio theory. Although Markowitz's work focused on selecting financial asset portfolios based on risk and return (Markowitz, 1952), the generalizability of Markowitz's portfolio theories has long been recognized as applicable for other domains of managerial practices (Gibson & Nolan, 1974). Building on the portfolio perspective, McFarlan (1981) adopted the ideas to portfolios of information systems projects in response to high project failure rates. While McFarlan (1981) still primarily emphasized the risk element on both the project- and portfolio-level, subsequent research has included a wider array of factors such as strategic fit and project synergies (Cho & Shaw, 2013; Cooper et al., 2001).

Up until today, research on PPM has been customized to fit many different portfolios. Ranging from portfolios for technology development projects (Cooper, 2006), radical innovation projects (Paulson et al., 2007), to IT projects (Neumeier et al., 2018), the field covers multiple project types and industries. Consequently, the literature on PPM for IT and technology portfolios is dense, with different techniques, methods, and practices proposed for best managing such project portfolios. However, as outlined above, the Volvo Car Corporation has experienced challenges with the high levels of uncertainties AI projects present. Furthermore, the tools used for some other project types typically rely on substantial and precise input data, something that is not always easily attained in AI projects. Thus, there exist a practical need for the development of new practices and tools, and to extend the research field of PPM to better suit AI projects. Indeed, specialized research literature on portfolio management practices for AI projects is still sparse, or even non-existent. Therefore, this thesis sets out to solve the problems the Volvo Car Corporation has experienced, and to contribute to the field by introducing a new customized framework for AI projects.

1.2 Purpose and research questions

The purpose of this thesis is to propose a framework of how PPM practices can be customized to fit the characteristics of AI projects. The framework intends to function as a managerial tool and therefore, the aim is to take a practical perspective during the construction of the framework. In order to do so systematically, two research questions have been formulated. Firstly, the study aims to outline the characteristics of AI projects from a PPM perspective, using commonly employed evaluation criteria from literature. Consequently, the following research question has been formulated:

(1) What are the main characteristics of AI projects when investigated from a project portfolio management perspective?

Secondly, once the key characteristics of AI projects have been identified, the study aims to investigate how these affect PPM practices. Additionally, the study aims to manifest the knowledge gained from the first research question into a framework. Thus, the following research question was formulated to enable these ambitions:

(2) How can project portfolio management practices be customized to fit the characteristics of AI projects?

1.3 Context and limitations

This study has been carried out in collaboration with the Volvo Car Corporation, hereafter referred to as Volvo Cars. More specifically, the study was conducted at the Advanced Analytics & AI department (AA&AI). This department was, at the time of the study, recently established as a centralized business unit responsible for driving AI initiatives and diffusing AI in the organization. However, as the name of the department implies, AA&AI also engages in other data science and advanced analytics initiatives. Although these projects could be more precisely described with other terms than "AI", they are still similar enough to be labelled as AI projects. Indeed, the term AI is ambiguous and encompasses multiple branches of science. Nevertheless, the thesis will from now on refer to all initiatives undertaken by the AA&AI department as "AI projects". This language is consistent with the everyday language used at Volvo Cars and was adopted to minimize confusion throughout this thesis. However, such a definitional decision merits explanation. In this study, the distinguishing factor used to define an AI project is that it carries out a predictive task of some type as its core activity, using statistical models and data. These models used for making predictions are all referred to as "AI models" in the upcoming chapters of the thesis, unless otherwise specified. Other project types than AI projects will collectively be referred to as non-AI projects, if not further descriptions are made. Furthermore, the AA&AI department does not contribute to research and development of new AI models, but uses already existing ones modified to suit the needs of the organization. Thus, the focus of the department's undertakings is to diffuse and apply AI, rather than to conduct research for new algorithms.

Consequently, some of the contextual factors limit the study from the beginning. While there certainly exist other limitations, the authors recognize two primary ones. Firstly, the study's scope is limited by the AA&AI department's projects. Although no project proposals explicitly are presented in the thesis, all analyzed projects and interviews within Volvo Cars are related to the automotive industry. Thus, the generalizability across industries of the study remains uncertain. Secondly, Volvo Cars is a complex organization with multiple factors affecting the PPM. While the authors primarily have relied on respondents from AA&AI, it is undoubtedly the case that other organizational factors will influence the PPM which not fully have been accounted for.

1.4 Report structure

The upcoming parts of the thesis are divided into the following six chapters: (1) Literature review, (2) Method, (3) Empirical findings, (4) Construction of the PPM framework, (5) Discussion, and lastly (6) Conclusion. The first chapter outlines the thesis's theoretical framework and provides an overview of previous literature within PPM. Additionally, a brief introduction to AI is included to equip readers with necessary terminology. Thereafter, the following chapter explains the research method used throughout the study. The third chapter outlines the study's empirical findings. Once these results have been presented, the next chapter synthesizes the findings into the framework for the PPM of AI projects. Lastly, the remaining two chapters contain the discussion of the results in relation to previous literature, and the conclusion of the thesis.

2. Literature review

This chapter presents a literature review to support the answering of this study's research questions. Initially, the chapter introduces the field of project portfolio management and the goals associated with it. This overview includes frequently used techniques and methods to realize the goals of PPM. Additionally, it includes a summary of a set of criteria crucial to use when evaluating projects from the PPM perspective. Complementary to the PPM perspective, a brief overview of the Stage-Gate model is included. Lastly, the chapter includes an introduction to AI in the context of large organizations.

2.1 Introduction to project portfolio management

Project portfolio management comprises a large set of activities and techniques to manage an organization's current and future projects (Cooper et al., 2002; Miller, 2002). Unlike the project management's (PM) focus on doing things right to ensure success on the project level, PPM is concerned with doing the right things by selecting an optimal set of projects (Cooper et al., 2000). Thus, PPM takes a centralized, high-level view over all projects, and evaluates them based on a larger set of factors than possible on the project level (Kendall & Rollins, 2003). This centralized perspective on projects enables a better view of synergies and makes it possible for managers to conduct risk and financial analyses of multiple projects together (Reyck et al., 2005). Consequently, PPM is not concerned with choosing projects that appear optimal in isolation, but instead with finding the best set that combinedly constitute an optimal portfolio (Cooper et al., 2002; Reyck et al., 2005).

To construct an optimal portfolio, the literature on PPM outlines several goals that the portfolio management team should aim to fulfill. One suggestion of a set of goals is described by Cooper et al. (2002) who emphasize that PPM should aim to maximize business value, ensure a balanced portfolio, align projects with strategy, and select the appropriate number of projects. Similarly, Miller (2002) emphasizes the importance of selecting projects to maximize the value, align the mix of projects with the strategic intent, and to continuously revise the portfolio to guarantee an appropriate mix of projects. The goals proposed by Cooper et al. (2002) are often accepted as essential to achieve with the portfolio management practices by scholars (Coulon et al., 2009; Killen et al., 2008).

To fulfill these goals, the PPM includes numerous activities and decisions necessary to undertake. Multiple activities have been proposed in previous literature (Cooper et al., 2002; Reyck et al., 2005), which Kaiser et al. (2015) summarize into three groups: identification and gathering of project proposals, project prioritization and selection, and continuous management of a project's ongoing fit with the portfolio. The identification and gathering of project proposals is often associated with the acquisition of input data about the project's business implications and technical feasibility (Archer & Ghasemzadeh, 1999; Cooper, 1990). Scholars often describe these activities as sequential and distinct from the prioritization and selection step (Archer & Ghasemzadeh, 1999).

The prioritization and selection of projects is associated with how projects are ranked between each other to ultimately form the optimal portfolio. Thus, the prioritization of projects is a prerequisite for the project selection as only a subset of all potential projects can be executed due to resource scarcity (Oh et al., 2012). Therefore, the project selection is an extension of the prioritization and is concerned with choosing the highest prioritized projects to maximize the value of the portfolio. However, the projects that the portfolio consists of are continuously changing throughout the projects' life cycles. Therefore, some scholars emphasize the ongoing management of the portfolio, with periodic reviews as one suggested managerial practice to use (Cooper et al., 1997b; Jeffery & Leliveld, 2004). The ongoing management of the portfolio aims to ensure the strategic alignment of the portfolio and to guarantee an appropriate project mix (Oh et al., 2012), which often is done through periodic reviews. These reviews are suggested to be performed with annual, semi-annual, or quarterly intervals by some researchers (Cooper et al., 1997b), but are often performed more frequently in high-performing management teams (Jeffery & Leliveld, 2004).

During the past decades, various suggestions on how the PPM activities best are conducted have been proposed. Suggestions include a vast array of methods and techniques that supposedly fulfill the main goals of the PPM, and assists portfolio managers in carrying out the previously outlined activities. Three major schools of approaches to PPM have emerged, according to Oh et al. (2012). The first category includes methods that use objective functions and constraints to optimize the portfolio on one or multiple factors. Thus, these approaches are best characterized as taking a mathematical optimization approach to PPM. Typical techniques within this category include linear, dynamic, or integer programming, which in theory are promising, however, seldomly employed or studied in practical contexts (Cooper et al., 1997a). The second category comprises prioritization-centric methods (Oh et al., 2012). The reasoning behind these methods is to prioritize and select projects based on numerous predefined characteristics that best maximizes the value of the portfolio (Blichfeldt & Eskerod, 2008). Techniques associated with the methods in this category can be divided into financial and comparative models. Financial methods prioritize projects based on a project's financial outlooks, while comparative models are more inclusive and based on characteristics that extend the financial analysis (Cooper et al., 2001). Lastly, the third category of PPM methods is best characterized as taking a strategic management approach to PPM (Oh et al., 2012). These methods complement the prioritization approach by emphasizing portfolio balance and interlinkage with the portfolio strategy (Oh et al., 2012). To reach the goals of the PPM with the strategic management approach, portfolio managers tend to employ techniques such as strategic buckets, portfolio maps, and various visualization tools (Wang & Hwang, 2007).

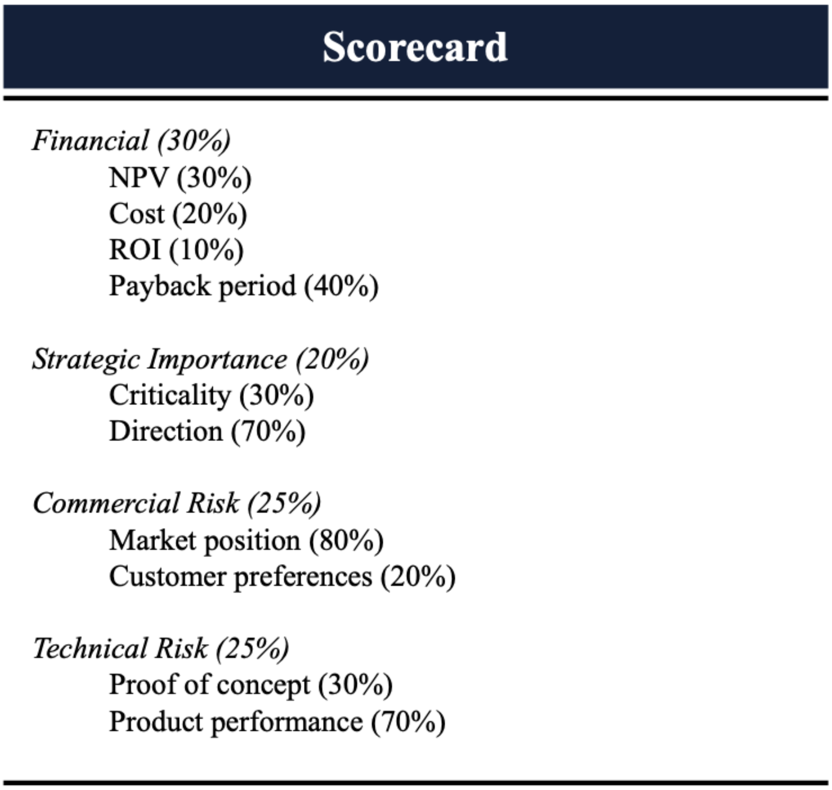
2.2 Techniques for project portfolio management

Even if there exists an academic consensus of the primary focus of the PPM practices, opinions diverge regarding which of the approaches to take to best fulfill the objectives. One of the reasons behind this divergence is that the context plays a vital role for the performance of the different methods (Blichfeldt & Eskerod, 2008; Christiansen & Varnes, 2008). For example, Blomquist and Müller (2006) show in their research that the success of the PPM is interlinked with the organization's ability to balance the organization’s external environment and type of projects. Similarly, Killen et al. (2008) conclude in their research that successful PPM practices need to be adaptive and change with the environment. Hence, the best approach tomorrow may very well be distinctly different from the one formalized today. Thus, the success of the PPM is interlinked with the organization's ability to learn and codify knowledge about the PPM practices and the context (Killen et al., 2008).

Regardless of which approach for PPM an organization employs, be it mathematical optimization, prioritizing, or strategic management, they all aim to fulfill the goals of PPM in one way or another. Therefore, depending on the organization’s context, it can prove to be favorable to combine methods that complement each other. Indeed, Cooper et al. (2001) show that a combination of techniques is beneficial for PPM and that best-performing firms use an average of 2.43 methods in their PPM practices. Therefore, in the upcoming sections, some of the most used methods, tools, and techniques for achieving the goals of PPM are presented.

2.2.1 Prioritizing projects

Financial methods are a set of commonly used techniques for scoring and ordering projects. Determining the priority with the help of these methods is accomplished using various financial metrics to assess the potential impact of a project (Cooper et al., 2001). Commonly used metrics include net present value (NPV), return on investment (ROI), and payback period. The NPV aims to determine the investment’s financial impact by discounting the project’s future cash flows. Similarly, the ROI aims to evaluate the investment’s efficiency by comparing the investment with the project’s financial return. In contrast to ROI and NPV, the payback period assesses the time until the investment becomes profitable. In addition to financial models, comparable models such as scorecards are widely used for project prioritization (Cooper et al., 2001). The most frequently used methods are scoring models, where scorecards are used to evaluate projects based on questions and performance estimates (Cooper, 1981; Miller, 2002). Once all questions and estimations have been specified, the score is calculated by weighting the relevance of each factor, as seen in Figure 2.1, and used for prioritization (Cooper, 1981). In contrast to financial methods, the projects are not exclusively evaluated based on financial metrics but may also include other factors, which can be weighted based on their relative importance (Miller, 2002).



Scorecard

Financial (30%)
    NPV (30%)
    Cost (20%)
    ROI (10%)
    Payback period (40%)

Strategic Importance (20%)
    Criticality (30%)
    Direction (70%)

Commercial Risk (25%)
    Market position (80%)
    Customer preferences (20%)

Technical Risk (25%)
    Proof of concept (30%)
    Product performance (70%)

Figure 2.1. Example of a scorecard used for calculating project prioritization scores, based on the scoring model proposed by Oh et al. (2012).

Out of these methods, the most commonly used in practice are the financial methods (Cooper et al., 2001). However, regardless of the less common use of scorecard methods, the literature emphasizes several strengths with them. As scoring models can include a wider assortment of attributes than financial metrics, they typically facilitate the achievement of more goals associated with the PPM. Consequently, it can contribute to both the balance and the strategic alignment of the portfolio (Cooper et al., 2002). However, the scorecard methods are not flawless as they are prone to subjective influences and do usually not consider interdependencies that exist between projects (Jugend & Silva, 2013).

2.2.2 Achieving a balanced portfolio

To achieve the goal of constructing a balanced portfolio, visualizations based on several critical factors for the PPM are commonly employed (Cooper et al., 2001). Scholars emphasize different parameters when evaluating the balance of the portfolio. However, frequently mentioned factors from both practice and literature are risk and reward, long- and short-term project duration, or high- and low-risk projects (Cooper et al., 2001). One popular visualization technique to illustrate the balance of the portfolio, frequently used to support portfolio managers in practice, are bubble diagrams (Cooper et al., 2001). The bubble diagram plots each project in the portfolio against several parameters which the portfolio manager strives to balance (Cooper, 1997a). Usually, bubble diagrams are two-dimensional, however, additional parameters could be represented through the size and shape of the bubbles as depicted in Figure 2.2. As exemplified by Cooper et al. (1997a), 3M employed a bubble diagram to support the balancing of their project portfolio by using the shape and size to depict the uncertainty associated with the estimates of the axis parameters.

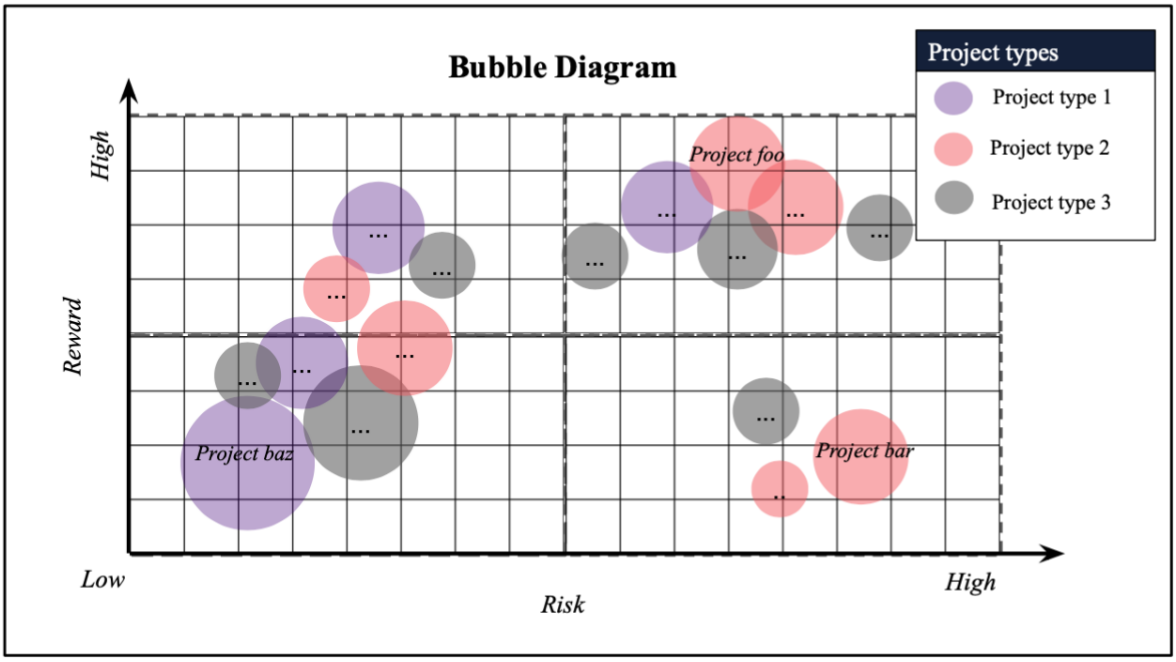


Figure 2.2. Example of a bubble diagram, which is a frequently used technique for balancing project portfolios.

When selecting the parameters for balancing, it is important to be aware of the interdependencies between the parameters and different project types. That is, the organization risks disfavor innovation projects due to the higher levels of risk these projects incur or favor large projects if the balancing procedure considers long-term projects (Meskendahl, 2010). Consequently, the parameters to balance the portfolio need to be related to the characteristics of the organization's projects (Meskendahl, 2010). Regardless of the factors used for creating a balanced portfolio, a necessary step is to evaluate the project-specific score associated with each parameter. If the project prioritization used a comparative method such as a scorecard, the resulting scores from this method could be used to evaluate the balance of the portfolio based on some of the included factors (Cooper et al., 2002).

2.2.3 Achieving a strategically aligned portfolio

One common technique to ensure the alignment between the portfolio and the overarching strategy is to use strategic buckets to divide projects into distinct categories (Cooper et al., 1997b; Cooper et al., 2001; Miller, 2002). The buckets represent the broad strategic commitments of the organization, for which a fixed amount of resources is allocated (Cooper et al., 1997b). Several frameworks for partitioning the projects to reflect the strategy have been proposed by scholars. One common suggestion incorporated by many PPM frameworks is Wheelwright and Clark's (1992) categorization. Wheelwright and Clark (1992) suggest a division based on project archetypes, defined by the degree of change the project presents to the organization. Others are inspired by Baghai et al.'s (2000) innovation-based approach, as depicted in Figure 2.3. With this method, projects are divided into three buckets, or horizons, based on if the project is contributing to the exploitation of current operations or the exploration of future business opportunities. Miller (2002) simplifies the partitioning into two categories, growth and survival, but also suggests that further focus could include areas such as enhancement projects, R&D projects, or utility projects. Regardless of the dimensions used for classifying the projects, the underlying idea is to reflect the business strategy through partitioning the allocation of resources based on the strategic orientation.

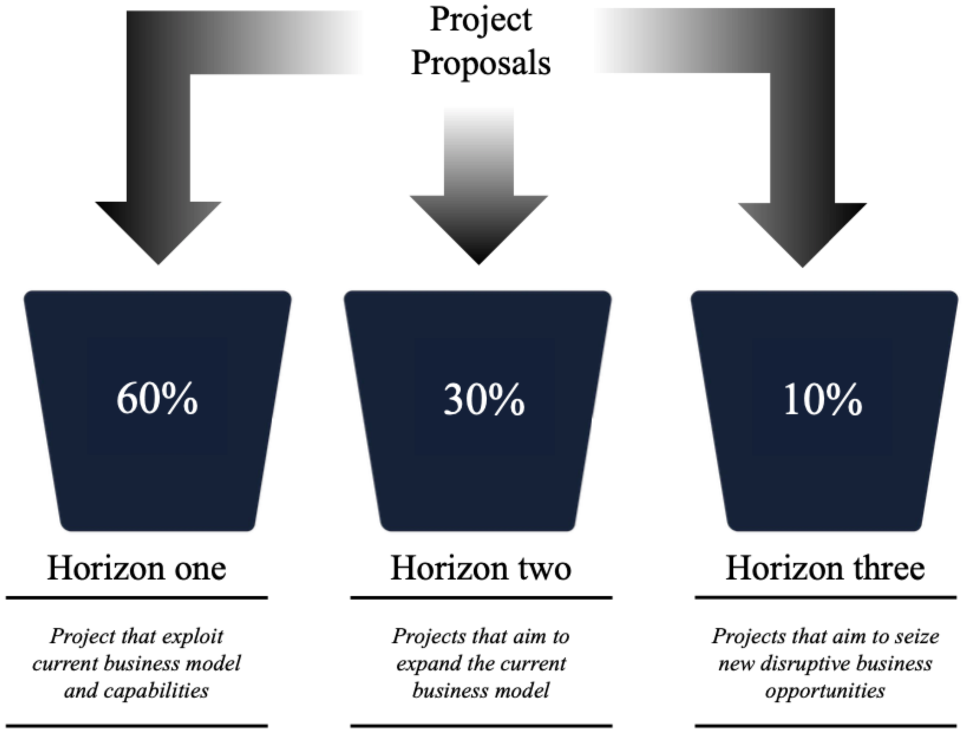


Figure 2.3. Illustration of the horizon-based approach for strategic resource allocation, proposed by Baghai et al. (2000).

In addition to ensuring a link between the strategy and project spending, the classification of projects can also assist portfolio managers when evaluating different types of projects (Cooper et al., 2002). Innovative product development projects can be troublesome to evaluate with the same criteria as used for large cost reduction projects, and vice versa. Consequently, categorizing similar projects in the same bucket allows for better comparisons and prioritization, since tailored prioritization techniques can be constructed to fit the intricacies of each project type (Cooper et al., 2002). However, the dimension governing the resource allocation should be carefully considered together with the parameter used for balancing the portfolio, since these typically are interrelated. Thus, depending on the dimension used for the strategic buckets, be it risk or innovation, it can have either a balancing or unbalancing effect on the portfolio (Oh et al., 2012). That is, if one strategic bucket aims to nurture very innovative projects, the balance of the portfolio would likely be skewed towards a high-risk profile.

However, the business strategy can be reflected through the portfolio by using other approaches than strategic resource allocation. Another suggested method is to integrate strategic criteria into scorecards for the project prioritization (Cooper et al., 2002). This approach allows for pursuing multiple different strategic goals simultaneously, and projects that fail to meet any of the strategic factors can be removed immediately (Cooper et al., 1997b). However, one challenge that exists when integrating strategic criteria into scorecards is to ensure that projects are evenly distributed to reflect all strategic commitments (Cooper et al., 2002). As explained by Cooper (2006), if financial metrics are assigned a high significance, technology development projects could unintendedly be killed early due to their many unknowns.

2.2.4 Accounting for project interdependencies

Stressed by Paulson et al. (2007), project interdependencies are essential to include when analyzing the mix of projects to ensure an optimal portfolio. Consequently, several models, often mathematical in nature, have been proposed to integrate the interdependencies between projects into the project selection phase (Abbassi et al., 2014; Jafarzadeh et al., 2018; Loch & Kavadias, 2002). One popular technique is the data envelopment analysis (DEA) (Jafarzadeh et al., 2018), which investigates the ratio between the input and output of a project to calculate its efficiency (Ghapanchi et al., 2012). The total efficiency of a suggested portfolio is then derived by adding the weighted average of all its included projects, taking interdependencies into consideration. The portfolio with the highest total efficiency represents the most favorable portfolio and should consequently be selected (Ghapanchi et al., 2012). While the techniques proposed in literature are theoretically viable, they rely on assumptions that input data for the models is available, or accurately quantifiable, something that seldomly is the case (Cooper et al., 1997b; Dickinson et al., 2001).

In contrast to mathematical approaches, methods from the prioritization-centric and strategic management approach do not include interdependencies to the same extent. Nonetheless, one comparative model suggested by Paulson et al. (2007) is to extend the scorecards to account for synergies. However, similarly the much of the literature on non-mathematical models, Paulson et al. (2007) do not explicitly explain how to quantify or identify them. Other techniques brought up by scholars include visual representations of projects, illustrating the interdependencies existent on a portfolio level. One example is a graph-based visualization of the portfolio, proposed by Dickinson et al. (2001), where projects exhibiting interdependencies are mapped to each other. However, constructing such a graph is time-consuming and therefore often disregarded as a viable method (Dickinson et al., 2001). Moreover, the hardship of quantifying interdependencies is also a challenge when constructing these visual representations.

2.3 Project evaluation criteria

As indicated by the goals and techniques in PPM, certain factors of a project are more important to evaluate than others. Scholars have suggested a vast number of evaluation criteria in previous literature (Cooper, 2006; Cooper et al., 2001; Jeffery & Leliveld, 2004; Meskendahl, 2010; Miller, 2002), often dependent on the type of projects that are being evaluated. However, four groups are nearly always included as primary project factors: (1) Reward and cost, (2) Risks, (3) Synergies, and (4) Strategy. Although these are reflected through the techniques outlined in the previous sections, it is important to provide an overview of the variants used for different project types. Consequently, this section covers some important perspectives on how the four project evaluation criteria have been presented in previous literature.

2.3.1 Reward and cost

There exists a broad consensus among scholars that it is important to include a project evaluation criterion that captures the absolute reward during the project prioritization and selection phase of PPM (Cooper et al., 2001; Meskendahl, 2010; Reyck et al., 2005). As outlined in the previous section, there exist multiple approaches for assessment of the financial contribution of a particular project including NPV, ROI, and payback period. However, literature diverges in terms of what to include in the criteria.

Some scholars rely heavily on the previously presented financial metrics as a means for measuring the reward that a project contributes to the overall portfolio (Reyck et al., 2005). However, other scholars are more inclusive in how they define a project's reward to the portfolio and organization. For example, Cooper et al. (2001) include aspects such as absolute contribution to profitability, technological payback, and time to commercialization. Another approach that includes more aspects than financial metrics to define reward can be found in the weighted scoring model presented by Oh et al. (2012), where NPV is weighted with factors such as cost, revenue growth and expected increase in absolute number of sales.

Furthermore, Cooper et al. (1997a) highlight that some firms choose to apply qualitative estimates of reward, as compared to the quantitative metrics presented above. These estimates are often used in the earlier stages of a project's execution when an excessive reliance on financial analysis can cause suboptimization. Such qualitative estimates can range from "modest" to "excellent" reward, simply to retrieve some systematized foundation for prioritization (Cooper et al., 1997a). Additionally, Cooper (2006) suggests that many financial methods are inappropriate for evaluating projects that aim to develop new knowledge, technological platforms, or technical capabilities. Instead, he suggests using rough estimates of the reward for such projects, since they typically can be characterized as high-risk with many uncertainties (Cooper, 2006). Similarly, Jeffery and Leliveld (2004) outline that a qualitative option value sometimes was included in the evaluation procedure of IT projects, to capture the value of future opportunities that the execution of one project enables.

2.3.2 Risks

While the techniques for balancing the portfolio reflect that a project's risk profile is important to consider, it is not unanimously referred to throughout literature. McFarlan (1981) highlights that two of the primary reasons for project failure are "*the failure to assess individual project risk and the failure to consider the aggregate risk of the portfolio of projects*" (p. 142). Furthermore, the author continues to outline that project size, the experience with the technology and the project's structure are three important dimensions which influence the risk of a project (McFarlan, 1981). Similarly, Reyck et al. (2005) show in their research that most companies who perform a risk analysis consider the technological risk of projects and the project's complexity prior to including them into a portfolio. Miller (2002) suggests in a similar manner to McFarlan (1981) that the level of detail not necessarily is the same when evaluating a project's risk on the portfolio level, compared to the evaluation on the project management level. Subsequently, the author provides examples of portfolio risks that may be evaluated, including technology risk, financial risk, scope or deliverable risk, schedule risk, and resources risk (Miller, 2002).

Another common perspective in previous literature views a project's risk in terms of probability of commercial or technical success (Cooper et al., 1997a). In the scorecard models developed by Cooper et al. (2001), a project's risk profile is scored based on several factors related to either the commercial or technical dimension. The factors include, but are not limited to, market maturity, regulatory impact, and competitive intensity in the commercial assessment, as well as technical gap, program complexity, and the organization's familiarity with the technology, during the technical assessment (Cooper et al., 1997a). Another similar definition of project risk is presented by Oh et al. (2012), where technical and commercial risk are used to evaluate a project's appropriateness for the portfolio.

Regardless of which factors to include in the project evaluation of risk, it is usually performed in a qualitative manner through, for example, questionnaires (Cooper et al., 1997a; McFarlan, 1981). However, the possibility to provide an accurate depiction of the risk associated with a project is related to the type of project. As emphasized by Paulson et al. (2007), radical innovation projects are by nature characterized as risky due to their high levels of uncertainties. Similarly, Cooper (2006) suggests that the assessments of risk in technology development projects must be altered to handle these high-risk endeavors.

2.3.3 Synergies

Since one of the main objectives of PPM is to maximize the value to the firm, it is typically not enough to evaluate projects in isolation (Meskendahl, 2010). As shown by Martinsuo and Lehtonen (2007), successful single project management is a prerequisite, however, not alone sufficient to achieve successful portfolio management practices. Therefore, interdependencies between projects need to be considered from the holistic portfolio perspective (Meskendahl, 2010). Previous scholars take different views on how to best evaluate interdependencies, with some focusing more on synergistic aspects and others on dependencies between projects. Additionally, various aspects of which interdependencies to consider are explored. For example, Pattikawa et al. (2006) show in their meta-analysis that technological synergies related to resources and skills have a large, positive correlation with the success of projects. Similarly, Verma and Sinha (2002) confirm those interdependencies but suggest market interdependencies, explained as the sharing of market knowledge between projects, as an additional source of potential synergies. Furthermore, from the perspective of IT synergies, the most commonly used classification differentiates between *subadditive cost synergies* and *superadditive value synergies* (Cho & Shaw, 2013; Tanriverdi, 2006). Cho and Shaw (2013) refer to superadditive value synergies as when the combined value is larger than the two stand-alone values of the units, and they arise from the notion of complementarity. Conversely, subadditive cost synergies emerge because of shared resources between the units and denote synergies which decrease the combined cost compared to executing the units in isolation (Cho & Shaw, 2013).

However, Lundberg and Thompson (1967) refer to resource interdependencies as inversely related project-wise. That is, if one project receives more resources, another project risk receiving proportionally less. This negative notion of interdependencies is shared in the extensive literature review conducted by Radszuwill and Fridgen (2017), who conclude that technical dependencies, in addition to resource dependencies, is a commonly used category of interactions in IT project portfolio selection. Technical dependencies emerge when one IT project relies on the output of a previous project, and may negatively affect the execution of subsequent projects (Neumeier et al., 2018). This notion of interdependencies is especially common in IT project portfolios due to the presence of many transitive dependencies (Neumeier et al., 2018). Such dependencies arise when a project *foo* depends on another project *bar,* and project *bar* depends on a third project *baz*, which indirectly creates a dependency between *foo* and *baz* (Neumeier et al., 2018).

2.3.4 Strategy

As agreed by scholars within PPM, strategy represents another crucial factor to consider when evaluating which projects to include in a portfolio. Therefore, assessing the strategic alignment of the projects is necessary to achieve the associated goal of PPM. Accordingly, many scholars have emphasized the criticality of a strategic analysis of each project. However, nuanced differences exist in which aspects to consider. Cooper et al. (1997b, 2001) stress the importance of assessing projects based on the project's fit with the strategy and the strategic importance of the project's direction. Meskendahl (2010) confirms the importance of these perspectives but underscores the necessity of a portfolio-level perspective when evaluating the strategic criteria. Therefore, Meskendahl (2010) stresses that every project needs to be included when considering the degree to which the project contributes to the business strategy. However, even though many scholars highlight the importance of evaluating a project's strategic impact before including it in a portfolio, knowledge of how to construct a theoretical concept of strategic fit is still limited (Srivannaboon & Milosevic, 2006). Moreover, assessing the strategic impact presumes that the notion of strategic success is defined. Strategic success is usually credited to the extent an action produces competitive advantages for the organization (Porter, 1987). However, the way through which this best is accomplished depends on the organizational perspective one adopts to evaluate competitive advantage (Dietrich & Lehtonen, 2005). Consequently, neither the concept of strategic fit nor the criterion for strategic success is well-defined. Nevertheless, commonly agreed upon is that strategic success is dependent on both environmental and intra-organizational factors (Dietrich & Lehtonen, 2005).

2.4 The Stage-Gate model

Although many methods and techniques for PPM are emphasized in previous literature, the information used in these does not exist at the portfolio level without performing activities at the project level. Many firms have adopted some type of project execution model which structure these project activities (Cooper et al., 2008). This can be necessary as a commitment to too many projects dilutes the focus and risks omitting critical activities, subsequently leading to unsuccessful project implementations (Cooper et al., 2002). One particular model that is widely adopted by industry, and often cited as suitable for feeding the portfolio-level with information, is the Stage-Gate model proposed by Cooper (1990).

Stage-Gate is a conceptual model for product processes that, in its simplest form, consists of stages and gates which facilitate identification, development and launches of new products (Cooper, 1990). Stages represent a collection of distinct activities responsible for moving projects forward while gaining new insights. On the other hand, gates constitute operational decision points with Go/Kill-decisions to take after each stage, and determine whether advancing the project to the next stage is deemed favorable (Cooper, 2008). Although the standard version of the Stage-Gate was developed for large product development projects (2001), later adaptations have been proposed to better fit novel PM methodologies and projects with different risk profiles (Cooper, 2008; Cooper, 2021; Edwards et al., 2019). However, common for all Stage-Gate models are that key activities are organized systematically, and that focus is placed towards those projects that show most promising results (Cooper, 2021).

This focus has important implications for project portfolio management. As argued by Amaral and Araújo (2009), "*The portfolio management team is normally concerned and overwhelmed with issues like the prioritization of projects and the continuous distribution of personnel from the different projects to overcome the urgent crises*" (p. 562). Consequently, finding a focus on the project level often aids portfolio managers in reaching the goals of PPM as well, by providing reliable data to feed the project selection tools (Cooper, 2021; Cooper & Edgett, 2003). Therefore, gathering the right information at the right time, which is often refered to as data integrity, is essential for a successful PPM (Cooper, 2008; Edgett, 2007).

2.5 Artificial intelligence in organizational contexts

Artificial intelligence (AI) is a broad science encompassing numerous research fields with its origin dating back to the 1950s (Buchanan, 2005). Since its inception, research within AI has advanced rapidly with broad adoption across numerous industries. As emphasized by business leaders, it provides improvements across a broad spectrum of functions from both operational parts of the organization to the managerial activities (Deloitte, 2017). Consequently, AI has received a lot of attention from organizations over the past decades. However, successfully reaping the benefits from AI requires new capabilities (McCarthy & Saleh, 2019). Acquiring these capabilities necessitates a strategic commitment directed towards AI. The extent to which organizations can successfully operationalize these strategic goals are linked to their PPM practices, as it is the manifestation of the business strategy (Cooper et al., 2001).

Another barrier for organizations to successfully implement advanced AI models, such as machine learning (ML), are the requirements it places towards new development practices. Even though AI projects often are compared with traditional software development, with well-established development processes such as DevOps and agile, they are not necessarily compatible. As emphasized by Lwakatare et al. (2020) "*Despite the ability of modern* *approaches in solving some of the problems faced when building ML-based software systems, there are no established procedures on how to combine them with processes in ML workflow in practice today.*" (p. 1) In contrast to classical software where the logic is encapsulated in the code, it is inferred through the data for AI models (Chollet, 2018). The differences between them necessitate novel approaches for developing AI.

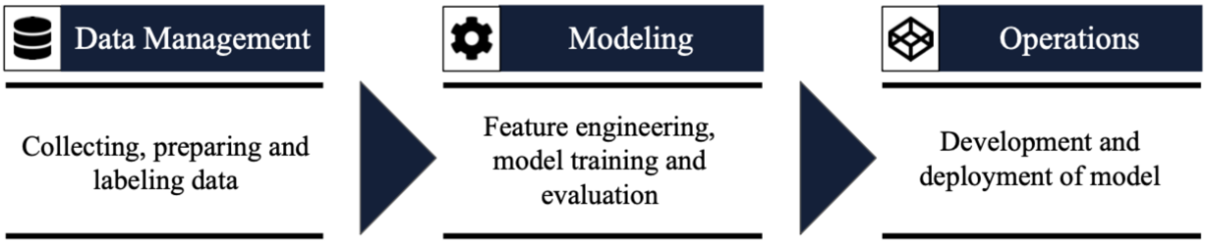


Figure 2.4. Conceptualization of the three stages of a typical machine learning workflow, as categorized by Lwakatare et al. (2020).

Lwakatare et al. (2020) highlight data management, modeling, and operations as critical, sequential activities that should encapsulate the development process of AI, as illustrated in Figure 2.4. The data management stage comprises activities related to collecting and preparing, or *cleaning,* data for future use. The output of these activities is typically a dataset containing the most important attributes of the data. These attributes, often referred to as *features* within data science, characteristics of a specific phenomenon or source (Bishop, 2006). Thereafter, the modelling stage is concerned with developing, or *training* various models based on the curated features (Lwakatare et al., 2020). A widespread family of models often developed are machine learning models. As the name suggests, machine learning aims to learn from data and constitute one of the subfields included in the term AI (Buchanan, 2005). Therefore, AI is often referred to as a data-driven approach, where various algorithms are combined with data to develop predictive models. Lastly, the operations stage is concerned with integrating the developed model for operationalized use.

3. Method

This chapter presents the research method used during this study. Initially, the chapter outlines the research approach that was used for the data collection and analysis. Thereafter, sections outlining the research quality and ethical considerations of the study are discussed. Consequently, the chapter is divided into four sections: (1) Research strategy and design, (2) Research process, (3) Research quality, and (4) Ethical considerations.

3.1 Research strategy and design

The selection of which research strategy to use in any study is dependent on numerous factors. However, it is often centered around the selection between quantitative or qualitative research (Bryman & Bell, 2015). While the two strategies differ on several aspects, they can usually be differentiated by the type of the data they rely on (Bryman & Bell, 2015). Qualitative research is concerned with words as the primary type of data (Bryman & Bell, 2015), and aims to understand and interpret the causes of a particular phenomenon (Gillham, 2004). Conversely, the quantitative research strategy is typically employed when investigating an effect, or a relationship, between one set of variables and an outcome (Bryman & Bell, 2015). Thus, it is tightly interlinked with quantification and measuring, to statistically determine such dependencies (Gillham, 2004). The choice of which research method to use depends on the problem at hand, and the chosen method should represent the most suitable way to solve it (Flyvbjerg, 2006). As stated in the first chapter, the purpose of this study is to construct a framework for AI project portfolio management. Therefore, the study requires a thorough understanding of the organization and AI projects at Volvo Cars. Consequently, it was clear that the qualitative strategy showed the greatest potential for the fulfillment of the study.

However, merely settling on a research strategy is not enough to answer any research questions. It is also necessary to decide on which research design to use (Bryman & Bell, 2015). This study required both an exploration across the organization and deeper investigations at the AA&AI department to fulfill the study's purpose. These requirements can be satisfied by the case study design, which provides researchers with a vehicle that allows for combining multiple qualitative methods (Knights & McCabe, 1997). Thus, as argued by Gilham (2004), case studies constitute a *main* method in which other methods and data collection techniques can be used. In this particular case study, qualitative sub-methods such as interviews, document analyses and observations were deemed suitable to answer the research questions.

3.2 Research process

This section outlines the processes used during the collection, processing, and analysis of the data. Consequently, it is partitioned into the two parts: (1) Data collection, (2) Data processing and analysis.

3.2.1 Data collection

Multiple sources of data have been used in this case study. To gain an understanding of the main characteristics of AI projects, a series of semi-structured interviews were conducted with researchers and lecturers within the field of AI. Additionally, to understand the organizational issues, the study involved both reviews of internal documents and interviews with managers at Volvo Cars. Thus, three major sources of data have been used to form the framework introduced in this study.

3.2.1.1 Sampling

The interviewees of this study were divided into two groups: (1) researchers and lecturers, and (2) managers at Volvo Cars. Consequently, the sampling process was also split into two subsequent processes.

The thesis's first research question intends to outline the characteristics of AI projects. The answer to this question depends heavily on whether particular emphasis is put on "AI" or on "projects". In this study, the focus has been put on the characteristics of artificial intelligence and how these affect portfolio management practices, rather than to focus on any specific type of project where AI is used. To find a suitable group to interview, given this focus, a set of sampling criteria were formulated: (1) the respondents should have practical experience with AI or have conducted research within the field, (2) the respondents should have practical experience with project management or project portfolio management, or have conducted research within the field. By convenience, one person who met these criteria and worked at Chalmers University of Technology was contacted and interviewed. Thereafter, the snowballing technique described by Bryman and Bell (2015) was exercised to find respondents who met the sampling criteria. This sampling technique led to six interviews and was terminated because of saturation in novel information and time limitations.

The second group of interviewees were sampled in collaboration with Volvo Cars. Since the AA&AI department during the time of the study was a newly established unit, the two main respondents from the organization were the same persons who helped formulate the study's purpose. Most of the interviews have been held either with one of the two respondents separately, or together as a group discussion. To gain an understanding of how other business units conducted their PPM practices, two additional interviews at other departments than the AA&AI were conducted. The respondents in these interviews were the Head of their respective department and were sampled purposively for answering specific questions within their area of expertise. Needless to say, this sampling was reliant on both the authors' own judgement and the organizational knowledge of the authors' supervisor at Volvo Cars, in order to select these as the respondents of the study.

In addition, the sampling procedure also covers internal documents. The sampled documents were selected in collaboration with Volvo Cars and could be categorized in two categories. The first category included documents outlining the current portfolio management processes that AI projects were subject to. These documents included questions, protocols and information gathering procedures that the managers at AA&AI deemed important to complete, prior to making decisions on whether a project should be executed or not. The second category of internal documents included AI project proposals. These documents included project descriptions and answers to the questions raised in the previously described documents. Some of the project proposals contained information on AI projects that, during the time of the study, were currently being executed and one example of a project that had been terminated.

3.2.1.2 Interviews

Following the structure of the sampling procedure, the interviews were categorized into two rounds. The first round of interviews was conducted with the purpose of assessing the characteristics with AI projects, thus providing data to primarily answer the first research question. These interviews were conducted with participants from the first group of respondents from academia. Since the interviewees represented slightly different fields related to AI projects in research and practice, it was deemed important to use an interview structure that allowed for varying discussions. However, equally important was to center the discussion around characteristics of AI projects in relation to PPM. Since this mixture of flexibility and systematization can be achieved through the use of semi-structured interviews (Bryman & Bell, 2015), this was the approach that was settled for. As explained by Bryman and Bell (2015), the semi-structured interview is often centered around a set of predetermined questions using an interview guide. The guide for these interviews was formed through a review of literature and discussions with the authors' supervisors at both Chalmers University of Technology and Volvo Cars. The central themes included in the interview guide (see Appendix A) were the four project evaluation criteria found in the literature on PPM: *Reward and cost*, *Risks*, *Synergies,* and *Strategy.* Additionally, the guide included some questions to gain a better understanding of how AI projects typically are executed, and the challenges associated with this execution. The rationales for the standardization were many, however, the primary reason was to facilitate comparisons of the answers with the descriptions of other technology dependent projects from literature, and between respondents.

All interviews in the first round were initiated with an introduction to the study's aim and the situation at Volvo Cars. Afterwards, the interviewers outlined that particular focus during the interview would be directed towards the four criteria. The interviewees were asked to comment on these and were free to provide their personal characterizations of AI projects as well. The round comprised six interviews with lengths ranging from 30 minutes to 70 minutes, with an average length of approximately 45 minutes. The interviews were recorded with permission to enable transcribing and content analysis afterwards.

The second round of interviews was conducted with respondents from the second sample group and focused solely on the managerial practices at Volvo Cars. The interviews aimed at answering the second research question by exploring the operations at the AA&AI department and other business units. Although these interviews were conducted in a semi-structured manner with specific themes developed prior to the conversations, less standardization between the different interviews was ensured. Thus, no singular interview guide was developed. However, suitable questions for each consecutive stage of the development of the PPM framework were covered instead. Additionally, for most of the interviews the interviewers prepared either a visual representation of the portfolio through a software solution, or a PowerPoint presentation, for the respondents to provide their feedback on.

The second round comprised 10 interviews with lengths varying between 30 minutes and 75 minutes and the average interview time amounted to around 46 minutes. The two interviews held outside of the AA&AI department were recorded as few chances to reconnect with the two respondents existed. However, during the interviews with the respondents from the AA&AI, active note taking was deemed more suitable to capture the major points of the back-and-forth discussions regarding the PPM framework.

3.2.2 Data processing and analysis

The recordings from the first round of interviews were transcribed upon completion. A content analysis of these interviews was carried out once all had been conducted. According to Elo and Kyngäs (2008), a content analysis can be performed on both qualitative and quantitative data and either in an inductive or a deductive manner. Since the first interviews were steered by the four evaluation criteria extracted from the PPM literature, these deductively guided both the conversations and the analysis in terms of which areas that were explored. Consequently, the content analysis of these interviews can be thought of as primarily deductive. However, the coding resulted in findings specific to AI projects, which emerged as interviewees were asked to freely characterize AI projects. These findings required open coding of a new factor: *AI-specific characteristics*. Additionally, some alterations to the deductive categories from the literature was necessary to fully describe the specifics of AI projects in relation to these factors. During the analysis, the transcripts were color-coded based on the four evaluation criteria found in literature, referred to as *factors*, and then partitioned into *categories* when differences were deemed significant. One example of this coding is shown in Table 3.1.

Table 3.1. Example of one factor and its associated categories extracted from the data in the first interview round

Factor	Categories
Risks	Data risks
	Development risks
	Deployment risks

A similar content analysis was conducted on the data from the second interview round. However, as this analysis aimed to create new knowledge within an area where previous literature was sparse, this analysis should be considered inductive (Elo & Kyngäs, 2008). The meeting notes were digitized and the recordings from the two interviews outside of AA&AI were transcribed. Additional data was extracted from a review of the internal documents. Thereafter, in accordance with the process outlined by Elo and Kyngäs (2008), the material was categorized based on the authors' interpretations during multiple rounds of re-reading and color-coding of word labels. All categories were collected and grouped together in factors, describing higher-level mechanisms in the PPM framework, and later into themes. This categorization was done iteratively and both themes and factors were collapsed and expanded when deemed appropriate to best reflect the content of the interviews. One example of this coding hierarchy is shown in Table 3.2.

Table 3.2. Example of one theme, its factors and the associated categories extracted from the data in the second interview round

Theme	Factors	Categories
PPM processes	Structured PPM process	Sequential process
		Integrated decision points
	Ordered PPM process	Resource efficient order
		Customer-centric orientation

To provide clarity to the reader, the upcoming chapters follow the same structure as the content analysis unveiled. However, the questions associated with the evaluation criteria *Strategy* did not generate enough data to constitute a separate section. Thus, the authors have abandoned the structure at some points. Furthermore, the authors have not been strict in only using data from one sample group to answer one research question. If respondents from Volvo Cars have provided informative data in answering the first research question this has been included as a means of triangulating the practical experiences from Volvo Cars with the research perspective. However, due to the division in sampling and structure of interviews in the two rounds, the bulk of the data relating to each question comes from the respective group.

3.3 Research quality

Lincoln and Guba (1985) propose that the evaluation of a qualitative study's trustworthiness is an important step in assessing the study's value. The evaluation of trustworthiness typically covers the following four criteria: (1) credibility, (2) transferability, (3) dependability, and (4) confirmability (Lincoln & Guba, 1985).

The credibility of a study refers to the degree of confidence in the believability of its results and is considered the most important factor for ensuring trustworthiness (Lincoln & Guba, 1985). The authors have continuously made efforts to increase the level of credibility of the study. Firstly, the majority of the findings were collected through iterative conversations with participants at Volvo Cars. This allowed for reassuring that findings from one interview were consistent with the information that the respondent at Volvo Cars conveyed. Credibility could also be increased through triangulation (Shenton, 2004). Triangulation has been leveraged throughout the study, which has been made possible from the multiple sources of data it rests on. By comparing the findings from the two interview rounds with each other, as well as with the internal documents, the authors have constantly ensured a credible understanding of the findings. Furthermore, the assessment of congruency between this study's results and existing literature is something that has been carried out in parallel with these triangulations, which is an aspect that Shenton (2004) argues typically increases the credibility of a study. Although measures have been taken to ensure the credibility of the study, there are certain aspects that could decrease the study's credibility. Restricted by the COVID-19 pandemic, the study has been conducted completely in an online setting. All interviews were conducted using video conferencing tools and both actors were present at all interviews. Participants could visually see each other at all times and no significant disturbances related to bad internet connections occurred during the interviews. Consequently, the authors subjectively deem that no significant drawbacks of interview results are associated with the online setting.

Transferability refers to how applicable the findings are in other contexts, or even in the same context at other points in time (Bryman & Bell, 2015). As outlined by Shenton (2004), there exist many strategies for reaching transferability, however, the authors should ultimately enable readers to make their own assessment of whether the findings can be applied in other contexts. Since the context at Advanced Analytics & AI quickly changes as the department scales, it can be difficult to ensure that the findings are transferable across time. Despite these issues, the authors have made efforts to ensure that the results are as transparent and objective as possible. Therefore, important contextual factors at the AA&AI department have been outlined in the introductory parts of the thesis. Furthermore, conclusions that are contextually dependent have been contrasted with findings from researchers or literature to emphasize that these potentially are dependent on factors specific to Volvo Cars. These efforts should allow the reader to assess whether the findings are transferable to other contexts.

Dependability is concerned with whether auditors would be able to follow the work of a study and repeat the research process (Bryman & Bell, 2015). Therefore, dependability can be difficult to achieve in qualitative research since the nature of many phenomena is dynamic and ever changing (Shenton, 2004). Nevertheless, authors should aim to achieve dependability of the results and can typically do so through detailed descriptions of the research methodology from a strategic perspective (Shenton, 2004). In this study, one guiding factor has been transparency in the methods the authors have used and the ways they were employed.

Confirmability is concerned with the neutrality of a study and to which extent the findings are presented without the authors' biases (Lincoln & Guba, 1985). Again, Shenton (2004) emphasizes that triangulation is important for ensuring that findings are kept objective. As previously explained, triangulation has extensively been used to ensure that the interview material is consistent with other documents and literature. Thus, to further increase the confirmability of the study, the authors discussed the methodology in general, and the content analysis in particular, together with their supervisor at Chalmers University of Technology prior to conducting it. These discussions aided in ensuring that the content analysis was guided by transparency and objectivity, even if the coding itself significantly relies on interpretations made by the authors.

Lastly, in the interest of transparency it should be mentioned that the study suffers from certain limitations that covers multiple of the aforementioned criteria. The sampling techniques that were employed during the study have to some extent relied on other people's judgement. At Volvo Cars, the author's supervisors appointed the two respondents from other departments. However, Volvo Cars is a large and complex organization in which it, as an external researcher, can be difficult to grasp which people will provide the most substantial viewpoint. The fact that the two respondents were the respective Head of the particular departments could serve for some evidence of independence between the participants. Additionally, the majority of the interviews have been conducted with a small number of individuals at AA&AI which makes the result heavily reliant on the opinions of these people. Here, the triangulation between the interview groups, literature and the review of internal documents has been important to ensure objectivity. The authors recognize that this influences the empirical findings, however, also recognize that these two respondents are the primary users of the managerial tool.

3.4 Ethical considerations

The authors of the thesis have actively worked to adhere to the expected ethical standards of the stakeholders, including Chalmers University of Technology, Volvo Cars, and the individual participants. Therefore, the implementation of the work has been based on several ethical considerations deemed necessary by the authors to satisfy the requirements. To guarantee the privacy and anonymity of the participants, several measurements were put in place prior to conducting interviews. Firstly, the authors offered each individual respondent the possibility to be anonymized. If the interviewee requested to stay anonymous, the authors redacted data that could be used to distinguish the interviewee's identity. Ensuring this high degree of anonymity also reduces the hazard of exposing statements that could harm the participant's current position. The authors of the thesis were conscious that the interviewees worked within an organization or institute, and thus, potentially could be harmed if the thesis's outcome were to become controversial. Additionally, to assure a reliable representation of the respondent's answers, substantial measures were directed towards collecting and annotating the data from each interviewee. For the interviews where the interviewee did not wish to be recorded extra precautions were taken when including these answers in the final thesis. Quotations were evaluated in detail several times to guarantee that quotes captured the essence of each statement without misrepresenting the current situation. Furthermore, statements that were highly dependent on the phrasing were rejected to ensure a fair representation.

4. Empirical findings

This chapter presents the empirical findings from the collected and analyzed data. The chapter has been partitioned into two parts, following the same structure as the research questions were outlined with. Consequently, the first section covers the respondents' propositions regarding the characteristics of AI projects, thus, establishing the bulk of the data to answer the study's first research question. Thereafter, the chapter includes the respondents' propositions about what characteristics the project portfolio management practices should be distinguished by. The chapter outlines these findings in the sections: (1) Characteristics of AI projects, and (2) Characteristics of the PPM for AI projects, respectively.

4.1 Characteristics of AI projects

This first section presents the data regarding the characteristics of AI projects. As explained in the previous chapter, this analysis was primarily carried out in a deductive manner utilizing the factors found during the literature review. However, some AI-specific characteristics were openly coded to capture the full picture of how AI projects affect portfolio management practices. The factors and categories found during the analysis are summarized in Table 4.1 below, which also governs the structure of this whole section.

Table 4.1. Factors and categories that characterizes AI projects according to the respondents of this study

Factors	Categories
Reward and cost	Indirect business impact
	Uncertain cost structure
Risks	Data risks
	Development risks
	Deployment risks
Synergies	Data synergies
	AI model synergies
	Development environment synergies
AI-specific characteristics	Data-dependent projects

	Unpredictable projects
	Experimentation-driven projects

4.1.1 Reward and cost

The characteristics associated with AI impacts the possibility to estimate costs and rewards of AI projects. Respondents mentioned the indirect business impact for AI projects and the difficulties to evaluate costs due to the uncertainty of the cost structure, as two critical categories associated with the factors *Reward and cost*. Thus, the major characteristics that affect cost and reward due to the characteristics of AI are categorized as: (1) Indirect business impact, (2) Uncertain cost structure.

Indirect business impact

Throughout the interviews, several respondents raised the issue of indirect business impact often associated with AI projects. As described by the respondents, the indirect business impact manifests itself in a difficulty to estimate the impact of a model. Usually, the positive impact experienced by the user is indirectly generated by the model and identifying the link between the model and the exact impact is not a trivial task. Additionally, several interviewees highlighted that estimating the business impact of a particular model required a detailed understanding of the context. Consequently, respondents from Volvo Cars emphasized the difficulty to estimate the precise impact of a project at an early stage. However, contrary to the respondents from Volvo Cars, one researcher stressed the fact that evaluating the impact of an AI model is also difficult during the deployment of the model. Hence, regardless of if the model is deployed or not, identifying and accounting for the true business impact is difficult as the technology in practice often is used to support or supplement other systems or decisions. Therefore, as expressed by one respondent: "*It won't necessarily improve the results for the digital [part of the] organization, but it will improve it for Volvo Cars.*"

Uncertain cost structure

Research respondents emphasized the difficulty of measuring the cost associated with AI development as a consequence of absence of information. One respondent from Volvo Cars confirmed this difficulty and highlighted that "*The cost of an AI-project is nearly impossible to measure.*" One critical component that has a significant impact on the cost is data. As emphasized by one researcher: "*70% to maybe 90% of the effort goes into the data management part; collecting, organizing, cleaning data and selecting all the features.*" One reason, highlighted by several researchers and confirmed by numerous respondents at Volvo Cars, is that available data is not always known in advance and requires substantial investigations. However, the extent of the investigations differs significantly dependent on how available the data is and how easy it is to prepare it. Therefore, the costs associated with the data management activities are often uncertain prior to starting the investigations. The hardship to estimate cost is also an effect of the vast prerequisites often associated with a successful AI project. This includes, as highlighted by several experts, investment in IT infrastructure that enables the execution of such projects.

4.1.2 Risks

The data collected during the interviews indicate that AI projects have a risk profile characterized by numerous AI-specific characteristics. The risk profile is multifaceted and is related to the (1) Data risks, (2) Development risks, and (3) Deployment risks.

Data risks

One aspect of risk, highlighted by both respondents throughout, is risk associated with data. As emphasized by the interviewees, the success of a project often relies upon the data being used. Useful data for most advanced models was often described as of high quality, quantity, and availability. Regardless of whether a project proposal is deemed valuable, from a business perspective, the absence of necessary data often results in early project termination. As emphasized by one researcher: "*You want to achieve something, but you are not confident that you will succeed because you don't know if the data is correct or enough.*"

A complicating factor is the lack of techniques and methods for assessing how ready the data is for training AI models with. As explained by researchers, the data readiness is often evaluated by training several models on the available data and comparing their performance with some pre-established baseline. However, as highlighted by respondents at Volvo Cars, the available data is not always known in advance, and necessary efforts often have to be arranged to identify the available data in the organization. This process of identifying and evaluating the available data is, as stressed by the respondents at Volvo Cars, a time-consuming activity representing a significant portion of the time dedicated to an AI project. Additionally, as expressed by multiple researchers, the quality of the data is partly determined by how well-developed the organization's IT infrastructure is. Thus, evaluating the data quality is both a time-consuming and resource-expensive activity that does not necessarily result in a positive return for the organization. Furthermore, as emphasized by respondents at Volvo Cars, there exist risks concerning the legal and ethical use of the data that have to be considered.

Development risks

One significant aspect of risk brought up throughout the interviews is the risk related to the development of AI models. The risk often occurs as a consequence of the inadequate possibility developers have in predicting the performance of a finalized AI model. Oftentimes, as emphasized by several researchers, it is only possible to evaluate the feasibility of the project through experimentation. This entails developing different models and comparing them with a baseline. The experimental approach does not necessarily ensure the completion of the project, but often leads to new AI project proposals. As expressed by one expert, the development of an AI model could be characterized as: "*You have a point A, but you don't really know where point B is*" Therefore, a risk exists that significant investments are made towards a project that ultimately does not reach the predetermined technical requirements. Consequently, estimating a precise time and resource expenditure is at best uncertain, as expressed by the respondents.

During one interview a researcher stressed that a common pitfall with AI projects is that the wrong model is used to solve a problem. Consequently, respondents stressed the necessity to continuously expand the technical capabilities of the employees. Moreover, the respondents highlight the importance of understanding domain knowledge as AI projects are cross-functional endeavors, requiring a broad spectrum of knowledge. If either of these pieces are missing, there exists a risk that the project will fail.

Deployment risks

Risk is not solely associated with data readiness or risk incurred during the development of the AI model. The succeeding stages of a project are also characterized by a high degree of uncertainty. Several researchers emphasized the risks that AI projects often are prone to in the later stages of the execution. In particular, researchers stressed the risk incurred when moving the model from a development environment to deployment. During this stage, there exists a hazard that the model will not perform sufficiently well as a consequence of potential differences between the data used during the training and data it will use during operations. However, as mentioned by numerous researchers, identifying these changes is not a trivial task and often requires dedicated resources to ensure that infrastructure and processes are in place to mitigate the risk.

4.1.3 Synergies

The characteristics of AI projects present many opportunities to share resources and knowledge across projects. Not only technical integrations can be reused, but also knowledge can be shared between multiple projects. Most of the interviewees highlighted synergies related to data, AI models, and using the same development infrastructure. Thus, the most prominent types of synergies in AI projects could be categorized into three major groups: (1) Data synergies, (2) AI model synergies, and (3) Development environment synergies.

Data synergies

The most frequently mentioned category of synergies among AI projects is related to data. Some respondents expressed that large possibilities exist to share the same data between different AI projects. Large costs are associated with the collection and preparation of data in order to make it appropriate to use in AI applications. Therefore, a cost-efficient solution can in some cases be to choose projects that share or reuse the necessary data to make certain predictions. Not only is this cost-efficient because of the direct cost reductions, but also because of the knowledge development regarding which processes can be shared. This was expressed by one interviewee in the following way: "*The methods, how to use and prepare the data for machine learning, is very important and this knowledge, these models and how to do these preparations can really help in the synergies of reusing data.*" Thus, since the data needs to undergo multiple processes between sourcing and analyses, directly knowing which processes to utilize for a specific dataset can reduce the cost of executing a particular set of projects sequentially. However, as some researches emphasized, the data synergies can also be related to knowledge concerning what data is available, and how to access this data in the organization. Data gathering often takes place in other parts of the organization than where it is used for analysis. Therefore, it can be valuable to reuse some datasets rather than searching for potentially non-existing data.

AI model synergies

Another frequently mentioned category of synergies specific to AI projects emerges from sharing AI models between projects. Just as in the case of data, where the synergies appear both through recycling the technical solutions and as knowledge regarding the use-cases, AI model synergies can appear. One respondent expressed this through: "*Reusing or reimplementing an idea could be seen as synergies, because if you have a model and you have an idea, which features of the data you can use and so on, then it's relatively simple: take another set of data and make the same starting model. This will give you results much faster than if you explicitly program it.*"

Thus, the codebases that AI models are built from could potentially reduce the costs of executing one set of synergistic projects. Not only can these be used in their entirety, leveraging the same data to make predictive analyses can be used to inform decisions in other projects, but by slight alterations, they can also be used in novel projects. Additionally, as described in the quote above, synergies between AI projects can exist from having an idea or knowledge about which models to employ for a particular task. That is, gaining knowledge of a new model through one project can significantly decrease the cost for other projects if the same techniques are applied.

Development environment synergies

The last synergy identified specific to AI projects, is related to the environment in which the AI models and data are produced. The respondents referred to the development environment broadly as the surrounding technical context, including development tools, documentation, and IT infrastructure, in which the data scientists construct AI models. Just like the data and AI models can present opportunities for reuse of some or all parts, the development environment can sometimes be reused for different parts of the model development. That is, if a software and hardware solution is deployed for transforming raw data into a suitable form for an AI model, the software and hardware could potentially be shared between multiple projects. For other AI projects, the tools and code for developing, testing, and deploying the AI models could be reused. Since much of the development time of an AI project is spent on training and testing the various models, sharing the resources between projects could present significant opportunities for cost- and time reductions. Additionally, as one of the respondents from Volvo Cars emphasized, good documentation about how to efficiently carry out these procedures is important to reduce resource expenditures.

4.1.4 AI-specific characteristics

In addition to the factors outlined above, there are certain properties that the respondents emphasized as especially distinct for AI projects. The analysis of the interviews concluded that AI projects can be characterized by three main characteristics, which all affect how the supporting organizational processes need to be formed to support the PPM for AI projects.

These characteristics can be categorized accordingly: (1) Data-dependent projects, (2) Unpredictable projects, and (3) Experimentation-driven projects.

Data-dependent projects

The thematic description which all of the respondents used as the primary characterization of AI projects is their dependency on data. Unlike other types of projects that benefit from data as information, AI projects process it as the primary activity. Not only do these data dependencies present increased risks and opportunities for synergies, but they also increase the demand for new capabilities within most organizations. Many AI projects encountered during this study have required cross-departmental collaborations, supporting IT infrastructure across organizations, as well as specific domain knowledge to interpret the performance and results of AI models. Thus, AI projects require many supporting factors to be in place for successful execution, due to their dependencies on data from all parts of the organization.

Unpredictable projects

Partly due to their substantial dependence on data and partly because of the uncertainties being present when developing AI models, AI projects often introduce high levels of unpredictability to the organization. As expressed in a large majority of the interviews, there are few tools to reduce or predict many of these uncertainties. Consequently, it is difficult to assess the probability of success at an early phase of the project. One researcher within the field of AI expressed this characteristic accordingly: "*Today, one of the weaknesses of AI is the unpredictability of the efforts. It's very difficult to predict how much effort will be needed to come to the final result. [...] So, there is a risk that the company puts a lot of effort towards something which will not give results.*" Another interviewee expressed that, in their experience, many organizations they had been involved with instead treated AI initiatives as activities without any predefined end goals. Not before one could be established with reasonable accuracy were the initiatives classified as projects, which often not was until the very end of the development cycle. Additionally, the unpredictability can often be traced to the difficulties in assessing the reward, time, and cost estimates of AI projects, as previously presented above.

Thus, in addition to characterizing AI projects as data-dependent, with all the intricacies that come with the characterization, the respondents also acknowledged AI projects as generally unpredictable. The effects of this unpredictability require changes to some managerial processes including PPM, as suggested by some respondents. These changes are primarily motivated by the fact that many traditional tools for diffusing technologies in large organizations are rendered obsolete by the hardship of accurately assessing whether the projects will be successful or not, and what impact the success will have on the organization.

Experimentation-driven projects

Lastly, respondents frequently emphasized the necessity of an experimental project design for AI projects, as few tools exist to predict which the most suitable AI model is for a particular set of data, prior to the deployment of it. Consequently, each AI project executed in an organization typically iterates through a number of steps before enough information has been gained to assess whether a task is feasible at all. For example, the feasibility of a model is usually assessed by developing a set of different and potentially suitable AI models. These models are trained and tested to see which model performs best on a selected set of data. Oftentimes, the data is experimented with as well, to determine which data features to include in the finalized model. Lastly, the final model is in many cases in need of iterative tuning to best be tailored to the chosen set of data. Thus, there are multiple steps of iterations in AI projects that all are in need of some experimentations. Consequently, many respondents expressed that the nature of AI projects is best characterized as experimentation-driven. Just like AI projects' inherent unpredictability and data-dependencies, this characteristic affects the design of managerial processes for AI projects. The experimentations require high levels of flexibility and formulated criteria for deciding on whether the experimentation should be proceeded or discontinued. Thus, consistent with one domain expert on project management for data science projects, some conventional ways of working are quickly dismissed and in need of replacement to effectively handle AI projects.

4.2 Characteristics of the PPM for AI projects

The following chapter presents the respondents' propositions about the characteristics of project portfolio management for AI projects. The collected data from the respondents has been classified hierarchically into appropriate themes, factors, and categories as summarized in Table 4.2, based on the similarities identified by the authors. The structure of the section follows the structure of Table 4.2.

Table 4.2. Themes, factors, and categories identified as important characteristics for AI project portfolio management

Themes	Factors	Categories
PPM processes	Structured PPM process	Sequential process
		Integrated decision points
	Ordered PPM process	Resource-efficient order
		Customer-centric orientation
	Continuous project reduction	Re-evaluation of portfolio
		Ongoing reduction of projects
		Prioritization
		Iterative development

PPM goals and characteristics	Realization of synergies	Achieve inter-project synergies
		Coordinate super-projects
	Ensure strategic alignment	Strategic resource allocation
		Integrated objective fulfillment
	Organizational environment	Transparency
		Politicized technology

4.2.1 PPM processes

The respondents in this study highlighted that the project selection phase of the PPM for AI projects best could be characterized as a set of sequentially ordered activities that aim to reduce the number of project proposals. The data can be divided into three categories that describe the project selection phase. These categories are: (1) Structured PPM process, (2) Ordered PPM process, and (3) Continuous reduction of projects.

4.2.1.1 Structured PPM process

One important aspect associated with the project selection process is the structure through which the projects are evaluated. According to the collected data, respondents highlighted the necessity of a: (1) Sequential process, and (2) Integrated decision points.

Sequential process

One manager highlighted that an unstructured PPM process could lead to a situation where "*[...] everything just flows together.*" During the same conversation, the manager emphasized that one consequence of an unstructured process is that the projects require an unreasonable amount of resources. That is, not being able to focus on a particular activity in a project could dilute the focus or lead to irrelevant activities being performed, leading to a potential waste of resources. A sequential structure, as suggested by the manager, implies that the project's activities are divided into separate, focused tasks. Each task aims to answer specific parts of the questions necessary to make an informed decision regarding if a project should proceed or not. Therefore, as expressed by one manager of the business unit: "*We answer the questions in an order so we, as early as possible can cancel the projects.*" The questions to pose during each activity varies with where in the project execution phase the project currently is, and could aim to answer whether the business case is attractive or if the project is technically feasible at all, as explained by the respondents.

Integrated decision points

Several respondents highlighted that the sequential process should be complemented with an active decision-making approach, supporting the resource allocation to each project. As expressed by respondents, the decisions should be integrated in the project selection phase and provide managers with the possibility to take data-driven decisions continuously. This, as formulated by the respondents, would facilitate that resources are directed to the most promising projects. Consequently, the PPM process needs to include guiding policies concerning which projects to discontinue or proceed with, based on the gathered information. Both experts and managers at Volvo Cars highlighted that the decision policies should be predefined and applicable for every project. A manager at Volvo Cars highlighted that such decisions sometimes need to be binary: "*AI or non-AI is something that you can determine early on. If there exist non-AI solutions, the project should be disregarded and delegated to another team.*" However, some decision points include multivariate decisions and need support from more advanced protocols as well.

4.2.1.2 Ordered PPM process

In addition to a structured PPM process, the empirical findings indicate that the process also needs to be arranged in a specific order to ensure an efficient project selection process. The order of this process should minimize cost and ensure customer focus from the very start of the selection phase. Therefore, the necessary characteristics the PPM should facilitate are: (1) Resource-efficient order, and (2) Customer-centric orientation.

Resource-efficient order

As specified explicitly by one researcher within the field of AI, the project selection phase for AI projects should accommodate a project management approach that allows for a problem and solution evaluation within each project. Once the problem and solution have been validated as critical for the organization, a more accurate evaluation of the project's impact can be estimated. Overlooking the problem and solution validation could lead to expensive solutions no one uses, as formulated by the researcher: "*It becomes a beautiful solution [...] no one wants to use because it solves something that isn't actually a problem.*" The importance for such validations prior to any development takes place was also stressed by respondents at Volvo Cars. The managers pinpointed that several project proposals they received did not constitute a large enough problem to solve, or that a non-AI solution could solve the problem just as well. The respondents stressed that evaluating the technical feasibility should be conducted after a valuation of the business value of the project. As highlighted by one respondent: "*You don't want to start developing a model or investigating systems before you have figured out the non-technical aspects*" Consequently, in addition to the requirements of a structured process, the PPM for AI projects needs to facilitate an order where non-technical characteristics are determined before the technical ones.

Customer-centric orientation

In addition to constructing a project selection process that allows each project manager to focus on the problem and solution before any development takes place, optimal PPM practices should facilitate a customer-oriented perspective, according to the respondents. As highlighted by both employees and experts, linking each project to the customer is desirable. As stated by one of the participating researchers, regarding the development of each project: "*You [need] to base yourself based on what the customer say*s" This emphasis towards the customer was also stressed by a manager at Volvo Cars who stated: "*I always want to have a connection between a project and the end-customer.*" Consequently, it is desirable to construct the PPM practices to promote this perspective throughout the lifetime of each project.

4.2.1.3 Continuous project reduction

The data further suggests that the PPM of AI projects needs to be characterized as a continuous process through which projects systematically and continuously are reduced. The respondents highlighted that this approach requires the PPM practices to allow for project re-evaluations, systematic prioritizing between projects, and to include a mechanism whereby projects are reduced continuously. Thus, the four main categories that were identified to facilitate a continuous project reduction are: (1) Ongoing reduction of projects, (2) Prioritization, (3) Iterative development, and (4) Re-evaluation of portfolio.

Ongoing reduction of projects

Several interviewees highlighted the necessity to take active decisions regarding if a project should proceed or be discontinued in the project selection phase, as new information was acquired. Thus, instead of taking a singular decision of which projects should be undertaken, projects should be dismissed continuously as new information becomes available. Consequently, the PPM should aim at facilitating this continuous reduction of AI projects. This idea was also highlighted by a domain expert who mentioned that: "*The problem is not that they have 100 projects, and they don't know how to pick the 10. The problem is, they don't have a process for winnowing down a hundred plus projects and get to a point where I have the most promising [...] projects which I want to double down on.*" The same respondent suggested one approach on how such a reduction could be formed: "*In the beginning you want to kill perhaps 75% [of the projects], in the next stage you kill 50%, in the stage after that you kill 25%, and you basically try to get rid of the 'bad ideas'.*"

Prioritization

An additional aspect raised by a majority of the interviewees from Volvo Cars is the necessity to develop a PPM procedure that includes a protocol for prioritization. Therefore, the protocol was perceived as a critical mechanism for determining which projects should receive funding. However, as expressed by one manager, comparing projects with each other is often perceived as difficult: "*How do you choose a project over another one?*" Thus, the findings indicate that the PPM of AI projects should assist managers in comparing one project with another. A practical suggestion proposed during the interviews was to calculate a score for each evaluation step to each project based on critical characteristics to make them comparable.

Iterative development

One aspect highlighted by multiple respondents is the necessity for AI projects to use prototyping to validate hypotheses regarding which AI model to use in a particular project. One researcher within AI management practices identified that prototyping should be combined with an iterative approach of development and evaluation. The respondent outlined that one suitable way to work with AI experimentation cycles is to establish performance baselines prior to the development of a new model. The newly developed model must then perform better than the baseline in order to proceed forward in the project execution phases. Otherwise, the model should be terminated as quickly as possible. The baselines could be in the form of trivial AI models or defined completely without any implementations. That is, the current performance of the manual procedure that the AI model aims to substitute or enhance could be used as a performance baseline.

The emphasis of iterative development using prototypes has also been expressed by respondents at Volvo Cars. At Volvo Cars, prototyping was integrated as part of the development in AI projects to validate the technical feasibility of the models and, more generally, the AI project. Moreover, the iterative element in this development was particularly stressed as it generally is not possible to determine which AI model to use in each project in advance.

Re-evaluation of portfolio

Projects that were deemed infeasible to execute by the respondents often lacked the right quantity or quality of the necessary data. Consequently, projects that showed great potential from a business perspective were put on hold to await the collection of data, or the development of other technical requirements, in the future. Therefore, respondents at Volvo Cars stressed the necessity to re-evaluate dismissed projects as technical requirements potentially became feasible over time. In addition to re-evaluations, there exists a need to bookkeep proposals that show promising possibilities in the future. That is, as expressed by the respondents, dismissed projects that show potential should be documented and stored in a separate backlog.

4.2.2 PPM goals and characteristics

In addition to the need for a structured PPM process, respondents highlight the necessity of a PPM that achieves critical goals. The interviewees emphasized goals concerning capturing synergies between projects and aligning the portfolio with the strategy. Furthermore, interviewees stressed the significance of an organizational environment that supports important characteristics of the PPM. Therefore, the following section will provide a comprehensive picture of the following factors: (1) Realization of synergies, (2) Ensure strategic alignment, and (3) Organizational environment.

4.2.2.1 Realization of synergies

The interviewees in this study have emphasized that AI projects bring with them multiple opportunities for leveraging inter-project synergies. Consequently, respondents deemed it important that a framework for PPM of AI projects should facilitate the leveraging of such synergies. While there are many ways to practically accomplish this, there seems to be a consensus of two important activities that portfolio management should support. These two activities can be categorized as: (1) Achieve inter-project synergies, and (2) Coordinate super-projects.

Identify and exploit inter-project synergies

According to the respondents, the first synergy-related activity that the PPM for AI projects should enable is to allow for identification of synergies between projects. It is not always the case that these synergies are immediately evident in the early phases of the project selection phase. Thus, a one-time evaluation of synergies prior to the project selection could lead to unexploited synergies, and potentially the choice of a sub-optimal portfolio. The knowledge about which data, what AI models, and which type of development environment that will be used in a particular AI project is typically unknown at the earliest phases of the project. Consequently, trying to evaluate inter-project synergies is a difficult task at this point in time, and often requires experimentation. In response to this, the general consensus from the interviewees was that PPM for AI projects needs to be flexible enough to allow for the re-evaluation of synergies as information is gained. However, the PPM process still needs to be systematized to ensure that projects that are showing potential for sharing resources are executed together, according to the respondents.

In addition to the identification of inter-project synergies, it is also important that the synergies are exploited appropriately. Respondents often mentioned that the exploitation of synergies typically was expected to lead to total cost reductions when executing multiple projects together, as compared to if the projects were executed in isolation. That is, the cost of one project could potentially be reduced if another synergistic project has been executed prior, or in parallel, to it. The respondents suggested some practical tools for ongoing monitoring of synergies through visualizations of the project portfolio. However, regardless of practical techniques, an ideal framework for the PPM of AI projects should enable portfolio managers to exploit synergies between projects.

Coordinate super-projects

Another important activity associated with synergies is the coordination of AI projects that together can create a higher combined value than the stand-alone value of any singular AI project. One manager at Volvo Cars suggested that certain AI projects, although aimed at different parts of the organization, could be linked together through a macro-level project, or super-project. Thus, projects that contribute to the same super-project should be ensured to be chosen, or at least evaluated in a manner that reflects the combined value of the super-project, compared with projects that only contribute to a single application. One manager at Volvo Cars saw the coordinating mechanisms towards a set of super-projects as an important step towards successful large-scale adoption of AI.

4.2.2.2 Ensure strategic alignment

The interviews also unveiled that it is important to consider how the PPM for AI projects can be constructed to ensure an alignment between the portfolio and the organizational, or departmental, strategy. The analysis of the interview data unveiled two main mechanisms in terms of ensuring a strategic alignment with the selected projects. These mechanisms were categorized as: (1) Strategic resource allocation, and (2) Integrated objective fulfilment.

Strategic resource allocation

Some of the interviewees outside of Volvo Cars expressed that one functioning way to ensure that a portfolio of AI projects is aligned with an overarching strategy is to make use of strategic buckets. By dividing projects according to a predetermined criterion, the PPM can ensure that resources are allocated to AI initiatives that best reflect the strategic intent, and that the right mixture of AI projects is funded. One criterion that was suggested during the interviews was to consider whether an AI project contributes with an innovative growth opportunity, or if it enhances the current operations. This was expressed by one respondent as: "*So the way that you divide your resourcing is: At a very early stage, you take the ideas and you try to classify all of the ideas into 'Is this a horizon 1 idea – extending and defending the core business?' or 'Is this a horizon 2 idea – we already have a proven business that we want to accelerate?' or 'Is this a horizon 3 idea – that is basically intended to build a new business for the company.*" The budget for AI initiatives could then be partitioned based on the number of buckets, and each bucket's relative significance for the strategy, to reflect the organization's intention with AI. The respondents suggested that such an approach could be an effective way to stimulate the right mixture of AI projects to be undertaken and, thus, establishing a tighter linkage between strategic plans and the project selection.

However, while a mechanism for strategic resource allocation was not deemed unimportant at Volvo Cars, it was not emphasized as a one that significantly would affect the daily operations for selecting projects. Instead, the partitioning of the budget was an activity that was done during the formulation of the strategy. Since the portfolio was yet under construction, the partitioning of resources had no real effect on which projects that were undertaken from any specific strategic criterion today. Thus, the PPM for AI projects could potentially gain from a strategic resource allocation in general. However, ensuring alignment with the use of a mechanism as strategic buckets is something that seems to be more important as the portfolio of AI projects matures, as indicated by the respondents of this study.

Integrated objective fulfillment

Instead of a mechanism that ensures the alignment between the strategy and portfolio based solely on resource allocation decisions, the respondents at Volvo Cars emphasized an integrated approach for standardizing the comparison between different AI projects. The automotive industry meets many external demands, which can be formulated as objectives within the firm, that not necessarily are captured by the overall resource allocation presented above. For example, the previously mentioned resource allocation was typically referred to as risk- or innovation-based, while objectives such as sustainability and increased car safety were more prominent at Volvo Cars. By allowing for scoring of specific strategic objectives that are deemed more important than others, the comparison of such objectives can be performed on a daily basis. Thus, AI projects that are aiming to reach certain objectives should be prioritized over, or at least be comparable in the prioritization process, to AI projects that aim to achieve other objectives. This was exemplified by one respondent at Volvo Cars, through: "*In order to talk intelligently about carbon dioxide reduction in comparison with other objectives, we would need a scale that the organization needs to inform us about, so that we can compare a financial saving of 100 million versus carbon dioxide reductions.*" Simultaneously, the respondents emphasized that such weightings would need to be systematized to sustain coordinating activities on the portfolio level. Multiple suggestions for implementing a mechanism for objective fulfillment were brought up during the interviews. These suggestions included scorecard methods, balancing of the portfolio on certain objectives, and visualizations to balance the different objectives. The practical implementation might vary as will be explored in the upcoming chapter, however, the importance for objective fulfilment is indicated as essential for the PPM of AI projects.

4.2.2.3 Organizational environment

Lastly, respondents both from Volvo Cars and academia highlighted the importance to consider the surrounding organizational environment when developing PPM practices. As indicated by the collected data, PPM practices for AI projects could gain from being implemented with high levels of transparency. There are two primary reasons for this. Firstly, AI projects are still a rather novel phenomenon from the perspective of project and portfolio management. Consequently, the tools and processes used in these managerial tasks are far from perfect and, thus, often in need of explanations and evaluations. Secondly, AI related initiatives suffer from the risk of being absorbed by other business units if a politicized situation is present in the organization. A transparent and systemized process can aid in avoiding this. The data relating to these two subjects have been categorized in two categories: (1) Transparency, and (2) Politicized technologies.

Transparency

During the interviews with Volvo Cars and researchers within AI, several of the respondents highlighted that the PPM should strive to uphold high levels of transparency. From the perspective of managers at Volvo Cars, the emphasis regarding transparency was based on two central arguments. Firstly, a transparent process promotes the possibility to communicate the reasoning behind the project selection process. As highlighted by one respondent: "*You can see all the projects in one place. We can talk about it, and I can explain to the team why we have taken certain actions.*" Secondly, by increasing the transparency of the PPM process, the evaluation of the portfolio mix and performance can critically be performed. For example, if a set of projects are selected using one particular scoring method and the subsequent performance of the projects is unfavorable, there will exist a need to adjust the scoring method. Without a systematized and transparent project selection process it is difficult to determine which levers to pull on to increase the future portfolio performance. Thus, as suggested by a manager at Volvo Cars, transparent historical data associated with previous decisions is advantageous when modifying the method employed. That is, any changes to the scoring methodology could be closely monitored and evaluated through the portfolio it produces. Thus, the expected value could be substantial by increasing the transparency of the methodologies used in the PPM process for AI projects.

Politicized technologies

During one interview with a respondent who had worked with AI projects in several organizations, an emphasis was put on organizational politics as a critical concern for the success of diffusing AI. The interviewee highlighted multiple failed attempts to establish AI initiatives due to political forces between different business units. As expressed by the respondent: "*In many organizations, there is a strong political process where people want to steal centers of excellence for their business purposes. So, what then happens is that the most powerful groups within the company, from a political force perspective, are the ones that steal* *most of the resources from a center of excellence. To the point where I have seen centers of excellence being completely absorbed by one of the strongest groups within the existing organization.*" The respondent followed up with emphasizing the importance to consider organizational politics associated with the project selection phase of AI projects in the following manner: "*Because why would everyone and their brother want to claim to their neighbors, at cocktail parties, and to colleagues that they are working with AI? [...] So, what you now see is that the biggest risk that the team has is that it gets too diluted, too politicized, and too much pulled into projects that actually don't matter. And that is what you have to help them protect themselves against.*" To mitigate the risk of absorption, the respondent suggested that the methodologies in the PPM processed should be well-defined and transparent. Moreover, the process needs to be standardized and structured, so that every project proposal receives similar treatments. Therefore, the respondent suggested that all projects should be ensured to go through the same PPM procedures and that this should be documented to decrease the risk of absorption.

5. Construction of the PPM framework

This chapter introduces a customized framework for project portfolio management of AI projects. The framework has been developed from the empirical findings and is complemented with portfolio practices from literature. In addition, practical considerations raised during interviews with Volvo Cars are included to exemplify the customizations for AI projects. The chapter is structured in accordance with the factors from the previous chapter, and the framework is sequentially constructed in three sections: (1) Structure and order of the PPM framework, (2) Support continuous project reduction and portfolio re-evaluations, and (3) Ensure link between AI strategy and portfolio. Lastly, a final section has been added to provide practical suggestions on how to accomplish a transparent PPM process, in (4) Transparency to reduce politicization of AI.

5.1 Structure and order of the PPM framework

The empirical data emphasizes that there exists a need for a structured and ordered process when conducting portfolio management of AI projects. Therefore, this first section focuses on the construction of the PPM framework in response to the factors *Structured PPM process* and *Ordered PPM process* from the previous chapter.

5.1.1 Structure that facilitates information acquisition

One of the main goals of PPM is to maximize the business value through the selection of a suitable portfolio (Cooper et al., 1997a). This goal relies on multiple activities in the PPM, however, the empirical findings indicate that two structural elements are essential to reach the goal when working with AI projects. Firstly, the project selection phase should be sequentially structured. Secondly, the structure should be complemented with integrated decision points.

As outlined by all participants in this study, prominent characteristics with AI projects are their high levels of uncertainty and unpredictability. These characteristics are partly a result of the dependency on data and the risks associated with it, and partly because of their unpredictability in terms of rewards and costs. As a consequence, it is practically impossible to determine which set of AI projects constitute the optimal portfolio during a one-time evaluation. Additionally, these characteristics render selection methodologies reliant on complete information about a project difficult to use at best, and widely inaccurate at worst.

Consequently, the framework proposed in this thesis suggests to focus on the information acquisition process, rather than on selecting a set of projects based on a one-time evaluation. Hence, instead of dismissing a majority of the projects, which often is dificult due to the particulair characteristics of AI, every project should be initiated. Thereafter, the project selection phase should be structured to support a successive collection of information about each project proposal, thereby successively reducing uncertainties. This would enable managers to make frequent and well-informed decisions regarding which projects to continue with, as information becomes available from investigation and experiments. Since information is collected through different means such as investigations and experiments, it is important to consider which information is most easily available. Furthermore, the structure needs to be complemented with active decision-making. Since the framework suggests to initiate multiple projects simultaneously, instead of selecting a few, the resource expenses will initially be larger. Thus, it is essential to integrate decision points to reduce the projects after new information has been acquired, in order not to waste resources on infeasible projects. Furthermore, by explicitly defining the requirements the project needs to reach, managers mitigate the risk of continuing with unsuccessful projects solely based on prior investments.

The combination of this extended project selection process and integrated decision points serves three primary purposes. Firstly, it aims to nurture a portfolio of AI projects that are likely to become commercial successes while contending with high levels of uncertainties. Secondly, it produces this portfolio of AI projects in a resource-efficient manner. Lastly, it presents portfolio managers with the flexibility to structure the project selection phase so that the most feasible sources of information are evaluated at each step and, thus, suits the characteristics of AI projects. In addition, as emphasized by Cooper (2008), it improves data integrity by ensuring that each project is passed through the same predefined activities, which in turn makes projects more comparable.

5.1.2 Resource-efficient and customer-centric order

The proposed framework suggests a structure where information sequentially is collected to support decision-making. However, the degree to which the structure can promote resource efficiency is related to the order of the sequence. If one source of information is more accessible than another and of equal importance, it should preferably be explored first. The necessity of an appropriate order is particularly important if there exists a large difference between the resources required for each subsequent step. As indicated by the risk associated with the data collection and AI model development, collecting an adequate amount of information regarding the technical feasibility is a resource-expensive task. In contrast, evaluating the financial opportunity associated with a project is not necessarily associated with equally high costs. Although an exact estimate of the financial impact is at best uncertain, due to the indirect business impact often associated with AI projects, knowledgeable stakeholders can often provide reasonable estimates. Therefore, as indicated by the empirical findings, the business case should be evaluated prior to other more resource-intensive technical aspects, and inform the decision maker whether the projects should receive further funding or not.

Consequently, the suggested PPM framework suggests an order in which a Business Case Evaluation is conducted prior to the Technical Feasibility Evaluation. This order also facilitates a customer-centric approach better than the opposite one, as outlined in the empirical findings. Ensuring a customer-centric focus can be achieved by establishing a clear understanding about the problem and a potential solution during the initial stages of the AI project. Retrieving such information first is particularly relevant for AI projects, since occasional overconfidence in the technology leads to proposals where AI is suggested as a default solution. Therefore, the problem and suggested solution should be validated prior to any experimentation and development.

5.1.3 First conceptual contribution to the framework

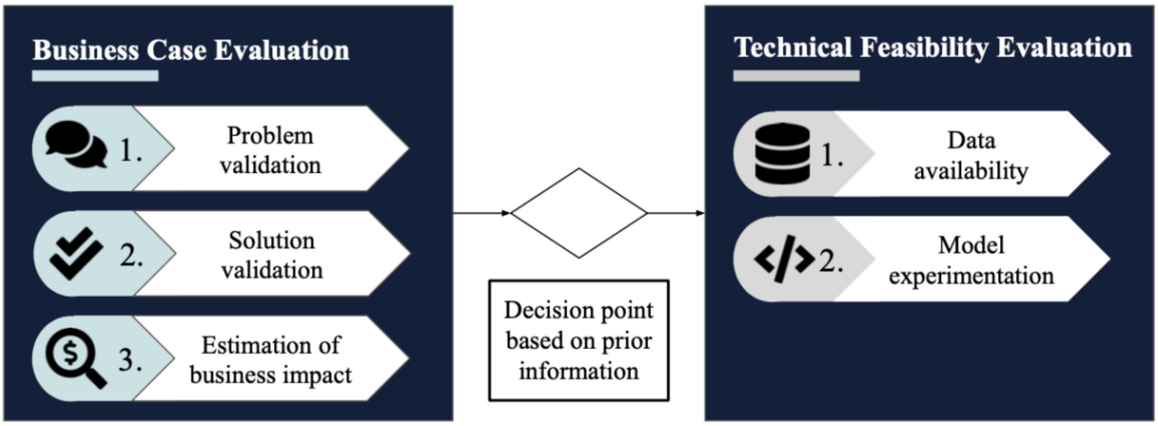


Figure 5.1. Conceptual framework of the first building block in the construction of the PPM framework for AI projects.

During the development of the framework with Volvo Cars, the project selection process was divided into the two main evaluation steps depicted in Figure 5.1. The first phase includes the Business Case Evaluation. This step consists of an initial evaluation of the AI project's problem and suggested solution, and a subsequent approximation of the potential impact of the business case associated with the project. The integrated decision point reflects the need for taking an active decision on which projects that are considered high-performing enough to proceed into the Technical Feasibility Evaluation phase, after the first evaluation. This second phase typically starts with an assessment of data availability as well as experimentation with different AI models.

5.2 Support continuous project reduction and portfolio re-evaluations

As suggested by the empirical findings, portfolio management for AI projects should facilitate an ongoing reduction of projects. However, this requires continuous re-evaluations of the portfolio to ensure that synergies are properly being exploited. Therefore, this section constructs the second part of the PPM framework which relates to the factors *Continuous project reduction* and *Realization of synergies* from the empirical findings.

5.2.1 Exit criteria and prioritization protocols

As outlined in section 4.2.1.3, the structure and order of the PPM process need to reduce the number of AI projects as information is gained. One suggestion to do so, proposed during this study, is by supplementing each decision point with an exit criteria. These exit criteria ensure that a certain number of projects always are reduced as progression is made in each project, thereby winnowing down the projects to a final portfolio.

However, as AI projects still are a novel phenomenon, there often exists a lack of reference projects to compare with. Consequently, it can be difficult for portfolio managers to calibrate the exit criteria to reduce projects into an optimal portfolio. That is, should the exit criteria be loosely defined the portfolio risks either becoming too large or too small for the available resources. Consequently, as expressed by some of the respondents, an explicit process for inter-project prioritization is valuable. Not only can a protocol for prioritizing projects between each other aid in the final adjustments of the portfolio, but it also enables managers to compare the projects based on data. This is important as it could help managers maximize the portfolio's business value and to construct a balanced portfolio in a transparent manner.

As reiterated many times, AI projects are characterized by high levels of uncertainties and typically require investigations or experimentations to acquire any information at all. Therefore, a protocol for prioritizing AI projects would need to make multiple projects comparable regardless of the type of investigation. While scorecard methods can constitute an appropriate method for assessing the business case of an AI project, it seldomly is viable as a stand-alone method for the Technical Feasibility Evaluation. The feasibility regarding data and AI model development is more appropriately informed through prototyping and experimentation, prior to scoring them. Many of the critical technical factors, such as data quantity and quality, can only be evaluated through an implementaion of an AI model built on that data. Once these models have been developed, suggested by some respondents, the technical feasibility can be assessed by comparing the model with a baseline.

5.2.2 Periodical re-evaluations of the portfolio

As highlighted by many scholars within the field of PPM, re-evaluating the portfolio is an important activity that should be performed periodically (Cooper et al., 1997b; Jeffery & Leliveld, 2004). The rationale for re-evaluating the portfolio could be summarized into two critical factors. Firstly, it serves as an important mechanism to ensure that the portfolio is updated with new information and facilitates the comparison of both active and new projects (Cooper et al., 1997b). Secondly, it allows the organizations to ensure an ongoing balance and a chance to consider relationships between projects (Cooper et al., 1997b). Since most information in AI projects is aqcuired through experimentations, and the lead times for these experiments vary a lot between projects, information gathering moves at different paces for different projects. Thus, frequent evaluations are necessary to coordinate the portfolio with up-to-date information as this becomes available from the project-level experiments. AI projects also present large opportunities for synergies and, as found through this study, are sometimes infeasible due to the current lack of data even if they present interesting business cases. This further motivates the inclusion of periodical reviews of the whole portfolio in the PPM of AI projects to maximize the business value.

The portfolio reviews for AI projects should support the characteristics of AI projects, as indicated by the interviewees. AI projects are unpredictable and experimentation-driven. Consequently, they might fundamentally change between each evaluation and synergies can emerge or vanish throughout the existence of the project. Thus, if one project is deemed feasible only because of its high interdependence with other projects, it needs to be re-evaluated if the associated projects are discontinued. Conversely, a project might look unprofitable on the project management level. However, from a portfolio perspective it can show great potential together with a set of other projects that share its resources. This is where the holistic perspective of the portfolio level is necessary. Consequently, the PPM should promote re-evaluations associated with the different phases.

However, the re-evaluation should not only ensure that synergies are considered between active projects. It should also make certain that new information regarding both active and temporarily paused projects is considered. It should also make certain that new information, regarding both active and temporarily paused projects that exhibit large business case potential but currently lack technical requirements, are considered. By including these projects during the continuous re-evaluation, the opportunity to maximize the portfolio value is further increased. Thus, the importance to re-evaluate AI projects seems to be of particular value due to the synergies they present and the fact that they occasionally are put on hold, awaiting larger quantities of data.

5.2.3 Second conceptual contribution to the framework

The first addition to the conceptual framework in this section is the formulation of exit criteria at the decision points. One researcher suggested that fixed percentages of projects could be reduced at each evaluation step, as indicated in Figure 5.2. Other suggestions included exit criteria based on the performance of an AI model compared to a baseline, or based on the information gained from previously executed AI projects. Regardless of the approach that is employed, Cooper (2008) stresses the importance of formulating exit criteria that sufficiently reduces the number of projects at each step. However, when formulating exit criteria for AI projects, the empirical finding suggests that it is necessary to construct the criteria in a manner that allows for iterative experimentation. That is, because of the nature of AI projects and primarily their reliance on experimentation, it is not merely enough to either terminate, proceed, or temporarily place projects on hold at each decision point. Instead, the exit criteria need to include the possibility to iterate the development cycle to allow for new experiments with alternative AI models or data when deemed necessary. This is especially important when conducting the Technical Feasibility Evaluation due to the uncertainty of AI-models. Thus, the second contribution to the framework is to expand the exit criteria to include the possibility to iterate into a new round of experimentation if the business case is intact and still attractive, compared with other projects. This expansion of the exit criteria is depicted in Figure 5.2.

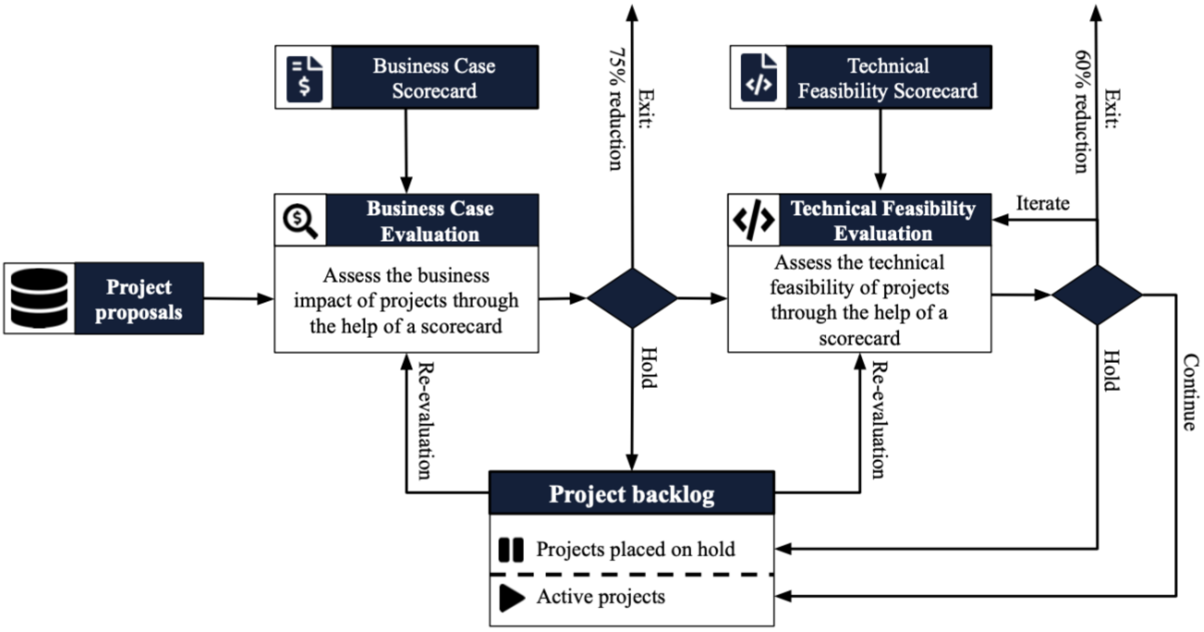


Figure 5.2. The second building block of the framework, including an order and structure that reduces the number of projects through decision points, re-evaluations and exit criteria.

In addition to formulating these exit criteria, the empirical findings revealed that it is necessary to facilitate prioritization of the projects. Therefore, the third contribution to the framework was to include prioritization protocols to ensure a systematized procedure. Due to the unpredictability of AI projects, many protocols suggested in literature require comprehensive information that was deemed infeasible to collect for AI- projects. Therefore, scorecards were developed that relied on rules of thumbs and estimations rather than exact predictions. An excerpt of the scorecard used for prioritization during the Business Case Evaluation is shown in Appendix B. These scorecards focused on the projects' financial contributionn, risk levels, and degree of strategic alignment, during this evaluation step. However, the scorecards could also be complemented with binary checklists that assess whether an AI solution is at all suitable to solve the validated problem, based on an expert's opinion. This could aid in overcoming situations where AI projects are suggested as a default solution. While the technical feasibility often is assessed through experimentations, a prioritization protocol could be formulated in a similar manner to score the outcomes of these experiments.

The value derived from these protocols provides projects with a score that could be used for the inter-project prioritization in each evaluation step. Furthermore, the scoring of each project would ensure that a transparent and systematized protocol is followed in each decision. Additionally, it supports data integrity, thereby increasing the focus and the chances of a successful PPM, as found by Edgett (2007). Lastly, it presents a way in which multiple diverging objectives can be quantified and made comparable with each other.

The final addition to the PPM framework in this section is the periodic re-evaluations. To ensure that the most advantageous projects are selected into the portfolio, the re-evaluation needs to include the latest acquired information. Therefore, re-evaluations occur continuously as new information is acquired and projects proceed forward in the development. During the re-evaluations, the acquired information guides managers in choosing which projects to proceed with by leveraging the exit criteria and inter-project prioritizations. The projects that are dismissed are either completely removed or placed on hold for future consideration. Alternatively, projects proceed to the next phase, or iterates for a new round of experimentation in the same phase again. When conducting re-evaluations and selecting which projects to proceed with, the empirical findings suggest that it is important to take a portfolio-wide perspective and include all projects to maximize the value of the portfolio. Thus, projects that previously have been put on hold, awaiting technical requirements or data collection, should be included, and compared with projects that currently are active.

The discussion with Volvo Cars concluded that visualizations of the portfolio could aid in monitoring which projects that were identified as exhibiting interdependencies. By coding and visualizing projects that either exhibit inter-project cost synergies, or contribute to the same super-project, these could be ensured to be considered during each re-evaluation. Furthermore, if the synergies between multiple projects are estimated, the supporting software solution could be used to provide scenario analyses of the portfolio if a particular set of projects were to be chosen. To ensure a balanced portfolio, literature emphasizes visualizations as a practical tool to balance the portfolio (Cooper et al., 2001; Wang & Hwang, 2007). This approach was confirmed as useful by Volvo Cars and hence a bubble diagram, as conceptualized in Figure 5.3, was suggested to identify synergies, and visualize the mix of various project types. Based on the dialogue with Volvo Cars, important parameters to include when balancing the portfolio would be the calculated prioritization score versus the risk associated with each project, during the Business Case Evaluation step. To approximate the risk profile of projects, a similar scorecard to the ones used during the Business Case Evaluation was constructed (see Appendix C). Additionally, different colors were suggested to aid in achieving portfolio balance, and sizes could potentially become useful to visualize the uncertainties in the prioritization score, similarly to 3M’s bubble diagram, as explained by Cooper et al. (1997a).

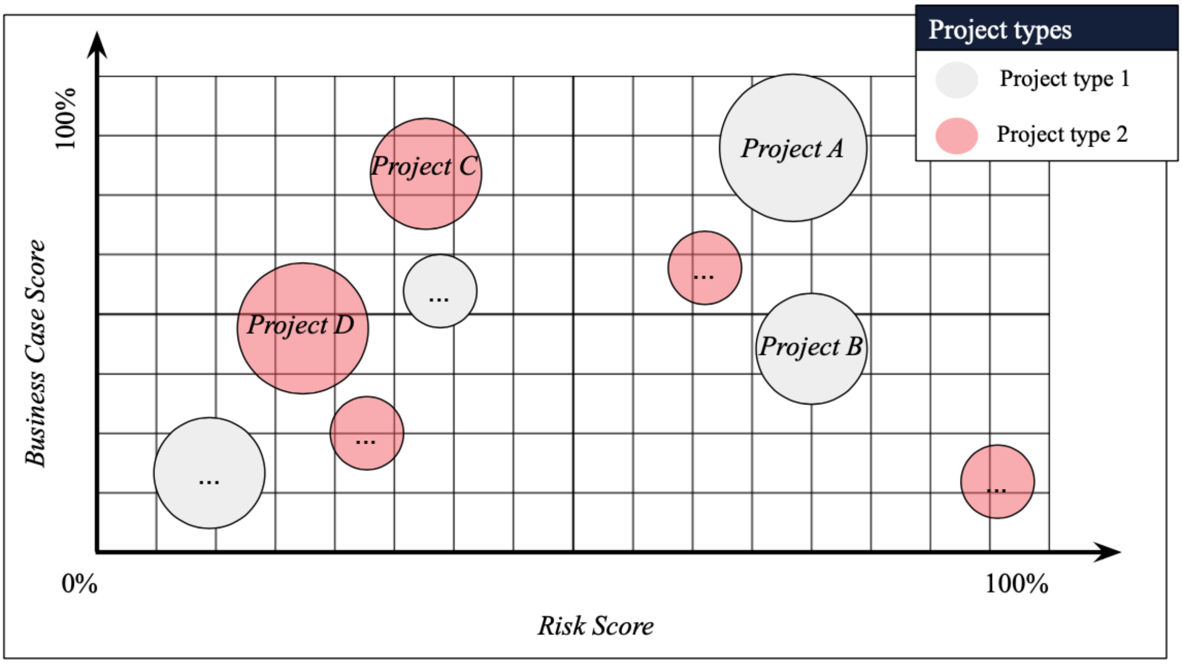


Figure 5.3. Conceptualization of a bubble diagram that could aid portfolio managers to determine which projects to reduce after each evaluation step.

Although no explicit interval for re-evaluating the portfolio has been established during this study, it is clear that re-evaluations play an important role in PPM for AI projects. Cooper et al. (1997b) suggest that portfolio reviews could be held semi-annually or quarterly. Therefore, a similar frequence, or higher as proposed by Jeffery and Leliveld (2004), could be a good starting point when determining the interval. However, as re-evaluations need to occur when new information is gathered, more frequent re-evaluations may be necessary AI projects.

5.3 Ensure link between AI strategy and portfolio

An ideal framework for the portfolio management of AI projects should, according to both the empirical findings and literature, align the business strategy and the portfolio. Therefore, this third section relates to the factor *Ensure strategic alignment* from the previous chapter and suggests some practical approaches associated with this procedure.

5.3.1 Strategic buckets and integrated objective fulfillment

As expressed by Cooper et al. (2001) “*Indeed portfolio management is the manifestation of your business's strategy – it dictates where and how you will invest for the futur*e” (p. 361), suggesting that PPM should facilitate an alignment between the strategy and portfolio. This viewpoint is important for a PPM process for AI projects as well, according to the respondents of this study.

As outlined by many previous scholars, the strategic alignment could be accomplished through the use of strategic buckets (Cooper et al., 1997b; Cooper et al., 2001; Miller, 2002). However, the strategic buckets implicitly assumes that projects can be categorized based on some predetermined criteria such as risk, project duration, or degree of innovation it introduces to the organization. Since AI still is novel for many organizations, it can be challenging to assign an individual project to any bucket without reference projects. Without prior projects, there are no clear divisions between projects exhibiting high or low levels of risk, or which degree of innovation it would bring. Consequently, for newly established portfolios with no prior history, techniques such as strategic buckets might not guarantee the alignment between the portfolio and strategy. This seems to be the general view regarding the use of strategic buckets of the respondents at Volvo Cars. However, as indicated by another interviewee, the use of strategic buckets can be useful for more mature portfolios of AI projects. Thus, integrating strategic buckets to align the portfolio with the strategy might be an appropriate measure for mature portfolios. However, it might seem superfluous for immature ones, according to the findings of this study. To allow for a flexible use of the PPM framework for AI projects the possibility to use such buckets has been included.

Nevertheless, the use of strategic buckets is not the only mechanism that can be employed in aligning overarching goals with the project selection procedure. As indicated by the empirical findings, the respondents from Volvo Cars deemed the pursuit of specific objectives, including safety and sustainability, important in their current operations. For example, AI projects that positively contribute to ecological sustainability or increase car safety should be made comparable with the pure financial impact of other projects. This can be achieved by integrating strategic metrics into the scoring methods used in the evaluation steps, to ensure that these are being pursued (Cooper et al., 1997b). This second approach can be combined with a strategic resource allocation to drive projects with a specific importance and fit for a specific strategic objective (Cooper et al., 1997b).

5.3.2 Third conceptual contribution to the framework

It could be valuable to include both strategic buckets and an integrated objective fulfillment approach in a PPM framework for AI projects, to ensure alignment between the strategy and the portfolio. However, the empirical findings indicate somewhat conflicting views of the effectiveness of the purpose-directed resource allocation. On the other hand, the integrated approach for objective fulfillment seems to work better for less mature portfolios. This mechanism also provides the inter-project prioritization score, which increases the transparency in the project selection process.

Thus, the addition to the PPM framework from this section is twofold. Firstly, consistent with the suggestion from the respondent who had experience working with mature AI portfolios, strategic buckets are integrated in the framework. Although this study does not make any further attempts to suggest the dimension on which the resources should be partitioned, or the relative spending size of each bucket, it could be useful to constrain the allocation of resources in a manner that reflects the organization's ambition with AI. This is further supported by Cooper (2006), who outlines that strategic buckets could be used for technology dependent projects as well. The depiction in Figure 5.4 emphasized this strategic resource allocation prior to the evaluation steps.

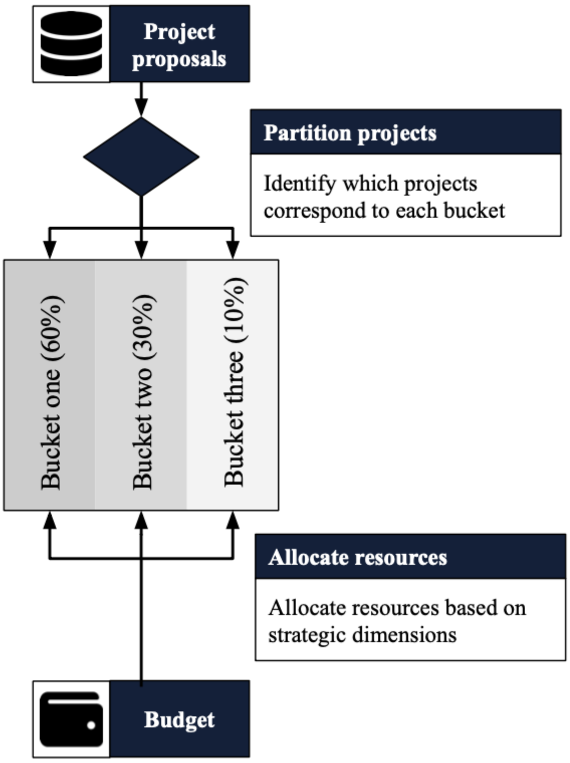


Figure 5.4. The last building block of the conceptual framework, which implements an integrated strategic bucket approach for the PPM. Percentages are only indented to illustrate the conceptual idea.

The empirical findings primarily centered around an integrated objective fulfillment approach and, consequently, a function was co-developed together with Volvo Cars during this study. Specific scoring cards were developed for certain objectives perceived as vital for the organization to pursue with its AI initiatives. The scoring cards were used to assess a weighted score of a project's impact and strategic importance on a specific objective. Thus, the approach is inspired by Cooper et al.'s (1997a, 1997b) idea, where strategic impact is integrated into the selection tool itself. Concretely, the section *Strategic Alignment* of the scorecards presented in Appendix B were used to assess scores of a project's objective fulfillment.

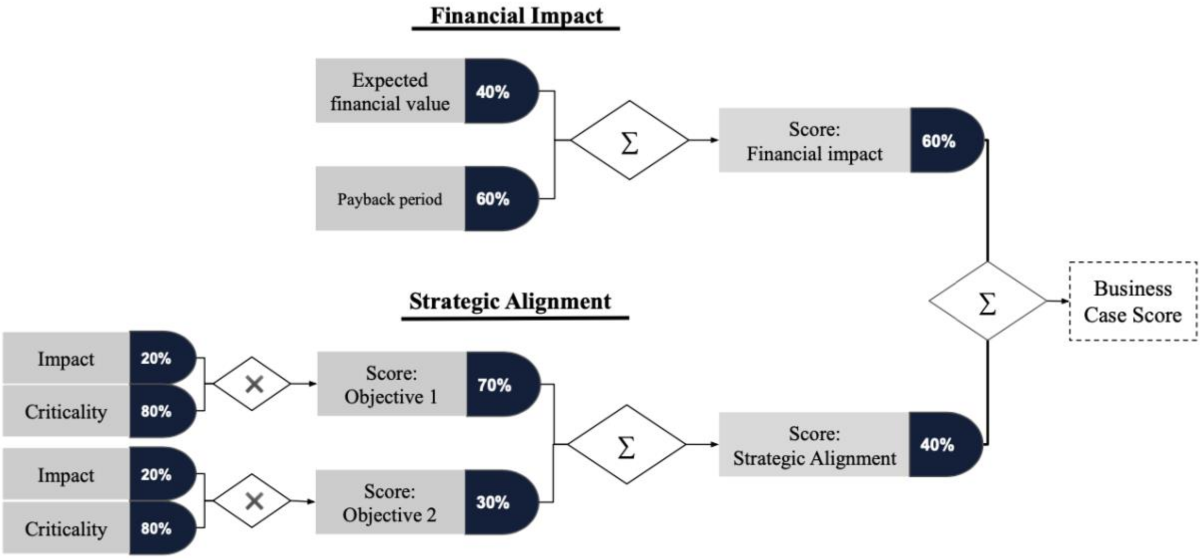


Figure 5.5. Illustration of the hierarchical, linear combination developed to derive the Business Cost Score from a scorecard. Percentages are only indented to illustrate the conceptual idea.

As illustrated in Figure 5.5, the Business Case Score was calculated by summarizing the financial and strategic score, respectively. To derive the strategic score, each objective the project contributed towards was evaluated and included. The size of the contribution was determined by estimating the impact and criticality the project had on that particular objective. To determine the financial impact, the total profitability and payback period were included, in accordance with previous literature and feedback from Volvo Cars. To provide a method to adequately compare parameters relative to each other, weights were included as depicted by the percentages in Figure 5.5.

The Business Case Score is used for inter-project prioritization in the Business Case Evaluation step, to favor projects that impact the organization both financially and strategically. While the fine tuning of the weights for each objective needs iterative configurations, the main goal of implementing such a function is to systematize the workflow of objective fulfillment in a transparent manner. Depending on the assigned weights of the objectives relative to, for example, the project's financial impact, the portfolio manager could expect that a tighter link between the portfolio and the strategy than if no considerations were to be taken to objectives at all.

5.4 Transparency to reduce politicization of AI

In addition to the mechanisms presented in the previous sections, the empirical findings also unveiled that the PPM process for AI projects should aim to be as transparent as possible. In response to these considerations, this section outlines some practical exemplifications on how to increase transparency that were used during the study. Following the same structure of previous sections and chapters, this section relates to the factor *Organizational environment* from the empirical findings.

5.4.1 Increase transparency

The proposed framework in this chapter is conceptualized based on specific characteristics summarized in the data. However, the PPM process exists within an organizational context in which decisions will be scrutinized. Hence, understanding the context is an important facet to understand how the PPM should be constructed. One contextual facet, as illustrated by the data, is the requirement of a systematized PPM process to ensure that projects are selected based on objective information rather than organizational politics. Therefore, the reasoning behind decisions needs to be clear, and the methodology through which the PPM is conducted needs to be well-established. Additionally, transparency is critical due to the uncertainties that AI projects are associated with, as the project selection otherwise risks being perceived as arbitrary. Therefore, transparency throughout the process ensures that the reasoning behind decisions are clearly communicated. Based on the necessity of transparency in the PPM for AI projects, the discussions with Volvo Cars concluded that a visual tool would support the communication by encoding the logic that should govern the activities and order of the PPM, in the visualization. The visual tool represents the platform through which the information is accounted for and decisions are based upon. The people who have access to the software can thereby clearly evaluate the process and question the decisions. However, encoding the process through a software solution does not by any means ensure transparency, but it is one step towards the transparency required to enact the PPM process.

5.5 Summary of the conceptual framework

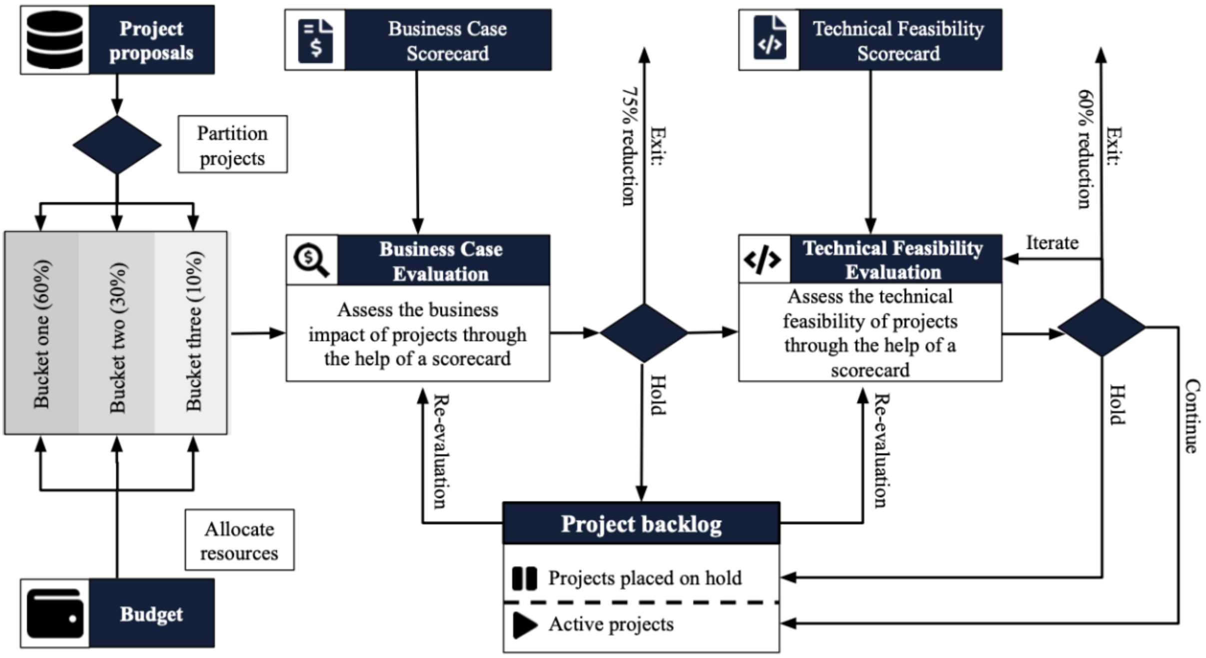


Figure 5.6. Complete illustration of the PPM framework.

This chapter has outlined essential practices which together constitutes a complete framework to manage project portfolios for AI-projects. To adhear to the aim of this thesis, and provide managers with a tool to handle such portfolios, the complete framework have been summarized in Figure 5.6.

6. Discussion

This chapter returns to answer the research questions the thesis set out to investigate and problematizes the empirical findings in relation to previous literature. Furthermore, the study's practical and academic contributions are summarized, and a brief discussion on contextual factors that merit considerations is included.

6.1 Characteristics of AI projects from a portfolio perspective

AI projects possess characteristics that render them difficult to manage from a portfolio perspective. As presented in the empirical findings, two of the primary characteristics are AI projects' heavy dependencies on data and their high levels of unpredictability. In addition, experiments are often used as a cornerstone for development, both to ensure performance of the AI models but also to assess whether the organization has all prerequisites to operationalize the models in deployment.

These characteristics become evident when considering AI projects from the perspective of the evaluation criteria *Reward and cost, Synergies,* and *Risks*. The findings related to these categories predominantly reflect the unpredictable nature of artificial intelligence. Concerning Reward, it is apparent that it essentially is impossible to accurately ascertain the size of the reward and costs of most AI projects. Additionally, the indirect business impact presents new challenges in constructing measurement techniques that reflect the true value the projects present to the organization. Moreover, the influence of synergies is emphasized in the literature, however, few details concerning the types of synergies that exist for AI projects are investigated. Similar to the taxonomy of synergies described by scholars such as Pattikawa et al. (2006) and Radszuwill and Fridgen (2017), the findings indicate a categorization of technological and knowledge-based synergies for AI projects. However, in contrast to prior literature, the findings emphasize synergies linked to data as critical. Although this study provides a suggestion to account for synergies by visually monitoring them, it is still necessary to define appropriate measurements to size them. Lastly, Risk is often discussed on a general level, however, this thesis paints a more nuanced picture of risk associated with AI projects, by partitioning the risk into three distinct categories. These risks require organizations to develop new tools to evaluate the current state of projects, and to determine when to discontinue them.

The prerequisites required to handle these AI-specific characteristics come in many forms and the empirical findings in this study makes no attempt to cover them all. However, some requirements deemed important for the portfolio management are obvious. Firstly, there exists a need for collecting and managing data within the organization. Consequently, this requires organizations to develop capabilities including supporting infrastructure, policies and governance structures to allow data to be shared across the organization. As data usually is specific for different domains it also requires that domain knowledge is accessible throughout the project development. The degree to which the need exists is dependent on both the specific

AI project and the context of the organization. However, regardless of the maturity and context of the organizations, they will inevitably encounter these needs in some shape or form when working with AI projects. Therefore, it is advantageous to consider whether the organizational structure facilitates cross-departmental knowledge and data to be shared. This should be done both before and during the enactment of AI project portfolios, to increase the project success rate.

6.2 Appropriate PPM practices for AI projects

The characteristics of AI projects do not only require organizations to acquire the organizational demands outlined above. They also require customized PPM practices to support the high levels of risks, coordinate for synergies, and measure rewards. The second research question of this study addresses these customizations and establishes that there exists a need to both incorporate appropriate elements from previous studies, as well as construct new ones specifically for the PPM of AI projects.

The empirical findings suggest that an appropriate PPM for AI projects should support an ongoing acquisition of information and facilitate frequent decision-making in order to construct a favorable portfolio. Thus, project selection methodologies that heavily rely on large amounts of information in initial phases are not well-suited for the selection of AI projects. Moreover, financial methods with metrics such as NPV or ROI are likely to result in suboptimal solutions, since the uncertainties of AI project render them inaccurate. Although Cooper et al. (2001) highlights that companies that rely solely on such methods tend to underperform either way, the characteristics of AI projects provide further motivation not to employ financial methods exclusively. Thus, the findings in this study support the statement by one executive in Cooper's (2006) study on technology development projects: "*It's like trying to measure a soft banana with a micrometer! Our evaluation tools assume a level of precision far beyond the quality of the data available*!" (p. 29).

Although some of the mathematical optimization approaches from previous literature take dynamic project logic and interdependencies between projects into consideration (Abbassi et al., 2014; Jafarzadeh et al., 2018; Loch & Kavadias, 2002), they do not seem to suit the characteristics of AI projects either. As explained by Oh et al. (2012) these methods rely on correct input data for optimizing. Since much of the development of the AI projects are done through iterative experimentations with both the data and AI model, it is rare that reliable information is readily available at the same point in time across multiple projects. Having to perform all project experimentation at the same time and at the same pace, in order to optimize the portfolio dynamically, is a task that is aggravated by the unpredictability of the experimentative outputs of AI projects. Therefore, this second approach for project selection of AI projects is suboptimal from a managerial perspective, as suggested by the empirical findings of this study. Additionally, the optimization techniques typically assume that either cost or reward can be approximated and optimized against (Oh et al., 2012). This implicit assumption quickly becomes a practical difficulty due to the indirect reward functions of AI projects, and the difficulties to estimate costs.

Instead, this study suggests employing an approach best classified as a strategic management approach (Oh et al., 2012), customized to fit the characteristics of AI projects. Even if this approach already is supported by the evidence found during this study it is further motivated by previous literature, or vice versa. For example, Cooper (2006) concludes that adapted financial methods and scorecards with rough estimates can enable enough flexibility for projects aiming to develop new technological capabilities or products. In addition, the scorecards should include multiple facets of the projects, such as technological, strategic and financial (Cooper, 2006). Furthermore, by combining multiple different techniques including strategic buckets, scorecards and balancing techniques, firms typically perform better than firms who only employ one method (Cooper et al., 2001; Jeffery & Leliveld, 2004). Many of these techniques and methods have been suggested as suitable for AI project portfolio management in this study. Therefore, the proposed framework could serve as an appropriate blueprint for the PPM of AI projects, something that is well grounded in PPM practices on similar projects.

6.3 Contributions and contextual remarks

The framework suggested in this thesis represents, to the best of the authors' knowledge, a first attempt at developing customized PPM practices for AI projects. The customizations include some notable contributions. Firstly, the structure and order of the framework merit further discussion. Previous research has emphasized order and structure of the PPM activities (Archer & Ghasemzadeh, 1999). However, seldomly has the reasoning been based on the intricacies and characteristics of a particular project type. The rationale presented in this thesis describes the properties that justify such structure and order for AI projects. The characteristics of AI projects that influenced the order and structure of the PPM most prominently were the uncertainties. Hence, an adequate amount of information is necessary to gather prior to the project selection. Previous research on PPM often implicitly describes information acquisition and project selection as separatable activities. Alternatively, methods are proposed which assumes an ad-hoc information gathering process, or that information is readily available. However, the findings from this study indicate the opposite as information collection, or experimentation, for AI projects represents a significant proportion of the total effort of the project. Therefore, similarly with the research on the Stage-Gate model, explicitly formulating processes related to project execution is essential for organizations. As shown in this study, the continuous information provided by these processes is imperative for the PPM. Therefore, a stronger coupling between the information acquisition process and the PPM process is warranted for AI projects. Thus, it is clear that to successfully implement the structure and order of the suggested PPM framework, a similar structure and order needs to exist on the project level. This could be achieved by adopting a Stage-Gate model for the project process as proposed by Cooper (1990, 2008), or a similar methodology. Thus, it is probably the case that the result from this study could affect the activities associated with project management as well. Furthermore, the thesis also adds to the existing knowledge base by suggesting how to manage experimentation-dependent projects during PPM decision-making. As explained during the construction of the framework, AI projects' novelty introduces uncertainties that best is handled through cycles of experimentations. Consequently, the framework includes a lot of flexibility and customized decision-making processes to support these cycles. This perspective has not, to the authors knowledge, been researched to significant extents.

However, there are some contributions in the study where practical suggestions only rests on limited empirical indications or previous literature. As Volvo Cars has not explicitly expressed a current need for strategic resource allocation to the same extent as previous literature has, few concrete suggestions have been provided on this point. Although one external respondent emphasized the appropriateness of such techniques for mature AI portfolios, other methods were deemed more important at Volvo Cars. Thus, the practical importance of techniques such as strategic buckets remains unclear. However, as the AI portfolio matures and reference projects become available, it is possible that the practical relevance of strategic buckets grows. Thus, it is worth problematizing the potential conflicts that may arise as resources stratify the reductive structure of the framework. Strategic buckets imply that resource allocation is superordinated to the global prioritization order. That is, a high-performing project in one bucket might not be selected over a sub-optimal project belonging to another one, if all allocated resources have been used for the first bucket. In this case, the reductive framework would lose its edge since it assumes that all projects are initiated in parallel. To solve the potential conflicts, the authors suggest developing different sets of evaluation criteria for each bucket as suggested by Cooper et al. (1997b). Thereafter, each bucket could be executed in isolation to ensure resource-efficient project reduction, using the structure and techniques proposed in this study.

It should be noted that many of the characteristics outlined in this study are not necessarily unique for AI. Some of the identified uncertainties and risks are likely as descriptive for novel technologies in general. Likewise, the hardship in assessing the business reward and approximate costs of projects is likely experienced for portfolio managers of IT portfolios as well. Nevertheless, many of the intricacies of AI projects which underpin these characteristics are probably more specific for AI. For example, the importance of data and its implications for unpredictability, uncertainties, and synergies are very prominent for AI projects and should be handled accordingly. Both the more prominent and specific characteristics for AI, and the ones shared with other project types significantly affect the framework suggested in this thesis. Even if the study does not discern to which extent each contribution of the framework is motivated by common or unique characteristics of AI projects, each must be considered and managed accordingly to successfully implement and diffuse AI in the organization. The findings indicate, similarly with many other project types, that PPM still plays a critical role in coordinating project prioritization and selection of AI project portfolios. Additionally, the goals of PPM are still important to guide the selection process to effectively diffuse AI in large organizations. However, customizations of the PPM structure, methods, and techniques are needed to best suit the characteristics and novel challenges AI presents. Ultimately, adopting a perspective of project selection as a crucial element of the PPM for AI projects does not seem to be effective. Instead, this study indicates that the portfolio construction with AI projects best should be characterized as a dynamic, yet systematized, project reduction process.

7. Conclusion

The purpose of this study has been to investigate the characteristics and challenges with AI projects from a portfolio perspective. The investigation was conducted at Volvo Cars, that recently organized a central department responsible for undertaking AI projects. Guided by two research questions relating to the characteristics of AI projects and how to best customize the PPM for these, the result of the study is a novel framework to assist the PPM for AI projects. Additionally, the thesis confirms parts of the previous literature within PPM and makes some novel contributions to the field.

The first contribution of the study is the mapping of AI project characteristics from a portfolio perspective. The empirical findings reveal that the reward and cost structures of AI projects are difficult to accurately estimate. Furthermore, the business impact from the projects is often indirect, rendering it challenging to define appropriate measurement techniques for estimating the value of each project. The risk profiles of AI projects are, in general, high and stem from three primary sources, including the data, the development of AI models, and the deployment of the models in an operationalized setting. While the risks are high, AI projects also present substantial opportunities for sharing resources between projects. Synergies are primarily expected to originate from sharing data, AI models, and the environment for developing the models. However, the synergies are not merely technical in nature, but could be seen as both knowledge- and resource-based. Lastly, the study finds that three characteristics are more specific for AI projects than projects in previous literature reflect. These characteristics define overarching properties of AI projects and include the projects' data-dependencies, the high levels of unpredictability they introduce, and the need for experimentations to execute them.

The characteristics of AI projects demand organizations to develop new capabilities such as supporting IT-infrastructure and well-functioning practices for sharing data across departments. However, they also require customizations of PPM practices. These customizations of the PPM practices constitute the study's second contribution to the field. While the order and structure of the PPM are necessary to ensure that no critical information is omitted, it is ultimately a perspective of continuous project reduction that needs to be adopted when constructing the portfolio. The PPM must also coordinate the evaluation of synergies and ensure that strategically suitable projects are favored during this reductive process. These findings have been summarized, resulting in a guiding framework for the management of AI projects as depicted in Figure 7.1.

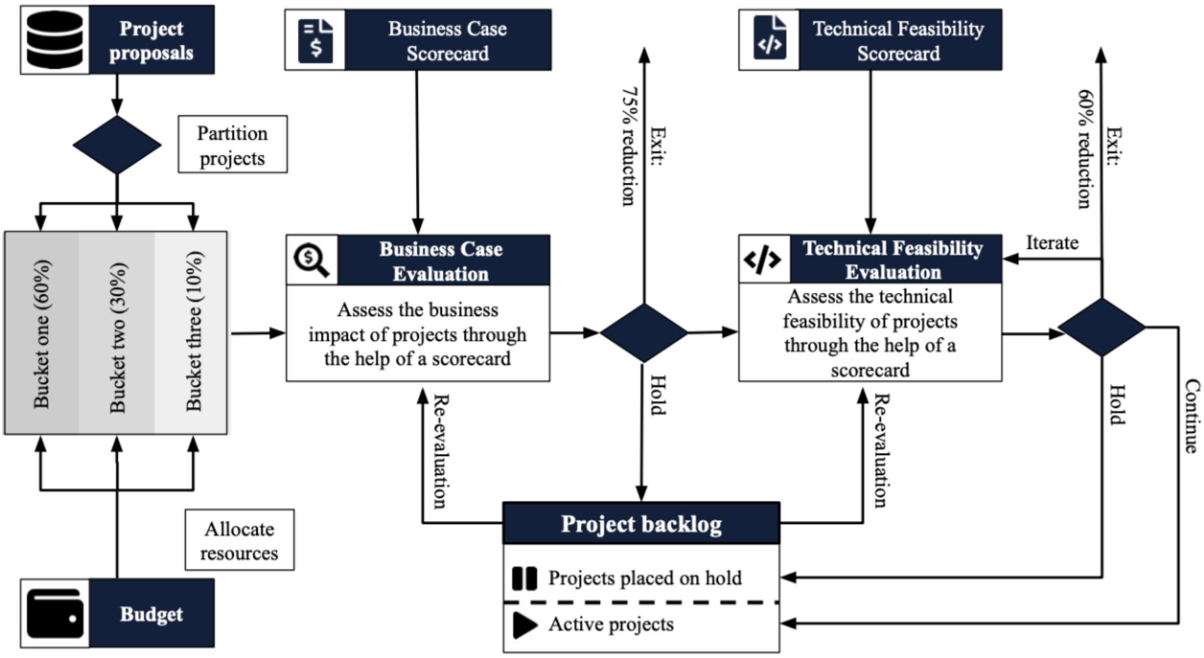


Figure 7.1. Suggested framework for PPM practices of AI projects.

The authors do not attempt to provide answers to all intricate questions about AI project portfolio management. Instead, this study should be viewed as a blueprint for how managerial practices could be structured, and as an indicator for important considerations managers should reflect upon. However, the authors have encountered one particular area where further research especially would benefit the understanding of PPM for AI projects. As expressed in the discussion, the study indicates that there is a need for frequent information transfer between the portfolio and project levels. However, the workflow remains somewhat undefined for AI projects, and many processes are left to develop in this bridge between the project- and portfolio-level of AI projects. Therefore, the authors suggest building upon the proposed structure in this study to influence these processes, thereby securing a tight interlinkage between the PPM and PM.

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Appendices

Appendix A - Interview guide

Introduction

1. Acceptance of recording and transcribing the interviews.
2. Introduction of the research questions and confirm that the interviewee has understood the contextual arena.
3. What is your personal definition of an AI project?
4. What is your background in data science and how have you been working with AI projects previously?

Characteristics of AI projects

1. What would you say are the significant characteristics by which an AI project could be described?

Reward and cost

1. What are the main characteristics in terms of reward?
2. How do these characteristics differ from rewards in non-AI projects?
   Potential follow-up areas to cover
   a. How could the cost be categorized in AI projects?
   b. How is the cost distributed in AI projects?
   c. Which benefits exist associated with AI projects in an organization?

Risks

1. What are the main risks associated with AI projects?
2. How does the risk-profile differ from non-AI projects?
   Potential follow-up areas to cover:
   a. Technical risks (data, development, deployment and integration)
   b. Organizational risks
   c. Commercial risks

Synergies

1. What are the main characteristics in terms of synergies between multiple AI projects?
2. How do these synergies differ from synergies in non-AI projects?
   Potential follow-up areas to cover
   a. Technical synergies (data, development, deployment and integration)
   b. Organizational synergies (knowledge, capabilities)

Strategy

1. Can AI projects be partitioned into categories that are advantageous for the organization?

2. What are the main strategic objectives that could be fulfilled by undertaking AI projects?

Challenges with AI project management

1. What are the main challenges to consider when undertaking AI projects in an organization?

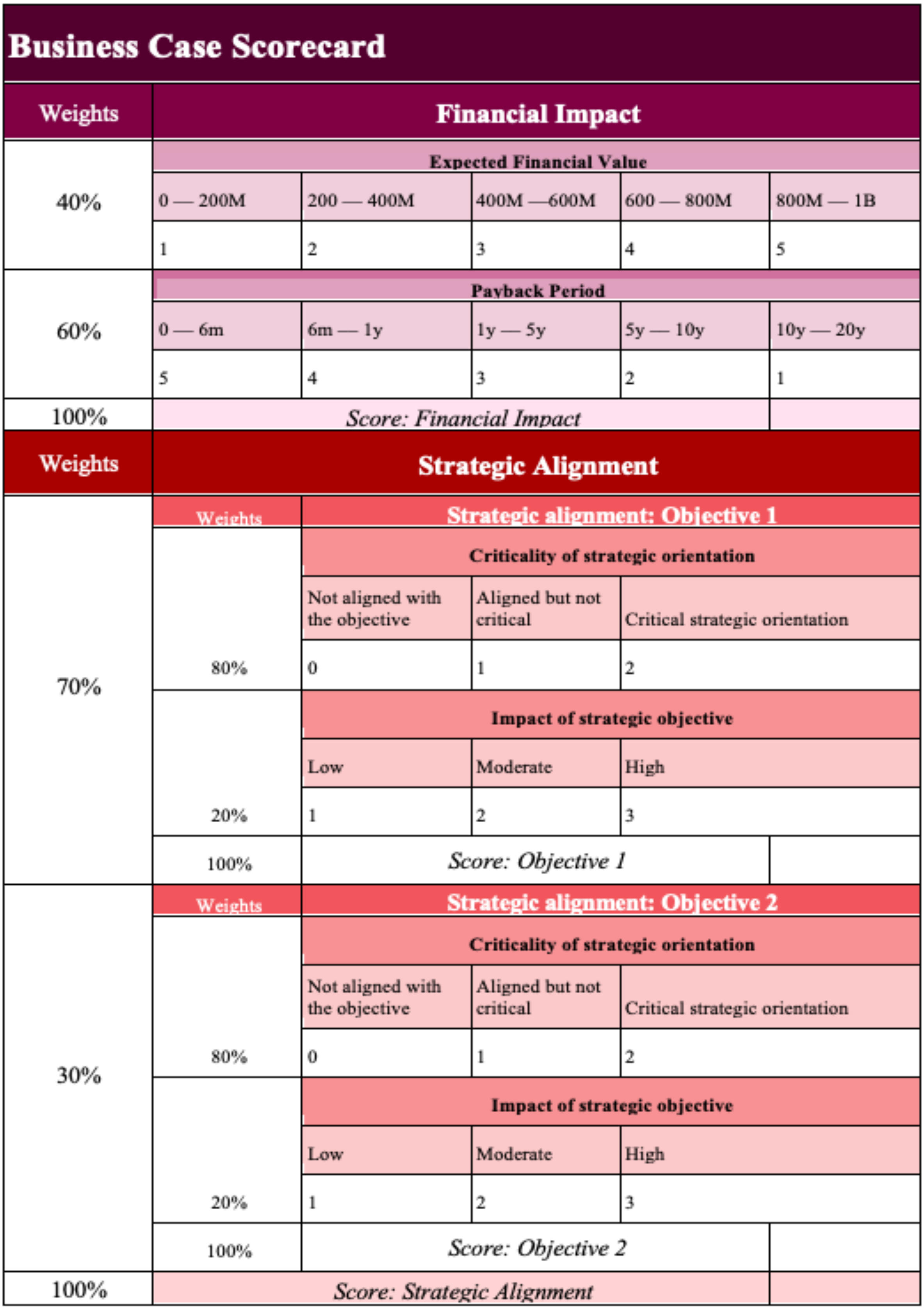
Sub-questions and themes

1. What capabilities do organizations need to develop in order to successfully realize AI-projects?
   Potential follow-up areas to cover
   a. In terms of processes?
   b. In terms of people?
   c. In terms of technology and infrastructure?

2. Where are the largest pitfalls for project failures of AI projects?
   Potential follow-up areas to cover
   a. On the project level?
   b. On the organizational level?

Appendix B – Business Case Scorecard

Note that the financial figures, the respective weights, objectives, and risks all have been stripped from confidential information.

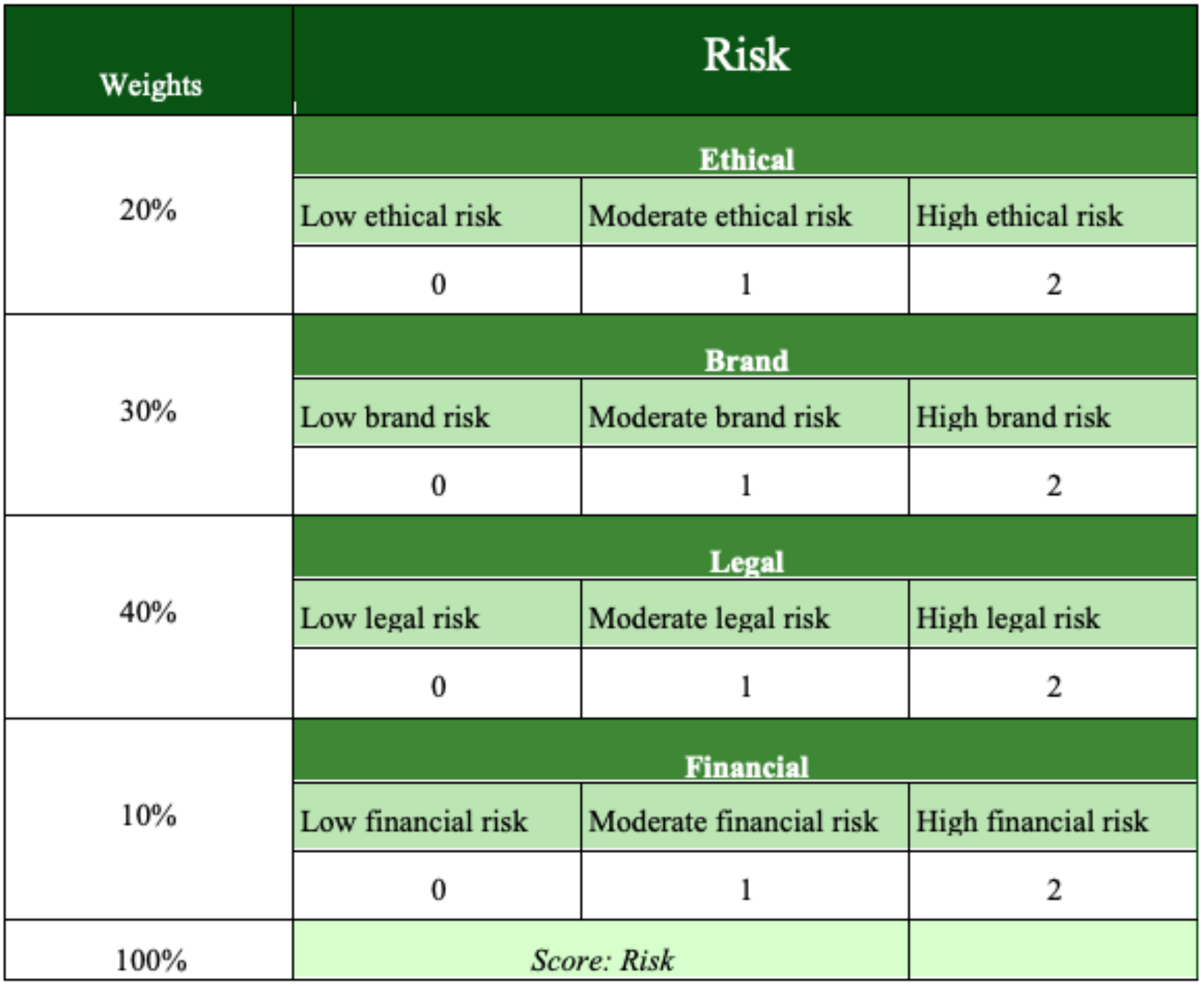


Business Case Scorecard

Weights		Financial Impact				
40%		Expected Financial Value				
		0 — 200M	200 — 400M	400M —600M	600 — 800M	800M — 1B
		1	2	3	4	5
60%		Payback Period				
		0 — 6m	6m — 1y	1y — 5y	5y — 10y	10y — 20y
		5	4	3	2	1
100%		*Score: Financial Impact*				
Weights		**Strategic Alignment**				
70%	Weights	Strategic alignment: Objective 1				
		Criticality of strategic orientation				
		Not aligned with the objective	Aligned but not critical	Critical strategic orientation		
	80%	0	1	2		
		Impact of strategic objective				
		Low	Moderate	High		
	20%	1	2	3		
	100%	*Score: Objective 1*				
30%	Weights	Strategic alignment: Objective 2				
		Criticality of strategic orientation				
		Not aligned with the objective	Aligned but not critical	Critical strategic orientation		
	80%	0	1	2		
		Impact of strategic objective				
		Low	Moderate	High		
	20%	1	2	3		
	100%	*Score: Objective 2*				
100%		*Score: Strategic Alignment*				

Appendix C – Project Risk Scorecard

Note that the types of risks, the respective weights, and the values of the scoring all have been stripped from confidential information.



Weights	Risk		
20%	**Ethical**		
	Low ethical risk	Moderate ethical risk	High ethical risk
	0	1	2
30%	**Brand**		
	Low brand risk	Moderate brand risk	High brand risk
	0	1	2
40%	**Legal**		
	Low legal risk	Moderate legal risk	High legal risk
	0	1	2
10%	**Financial**		
	Low financial risk	Moderate financial risk	High financial risk
	0	1	2
100%	*Score: Risk*		

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