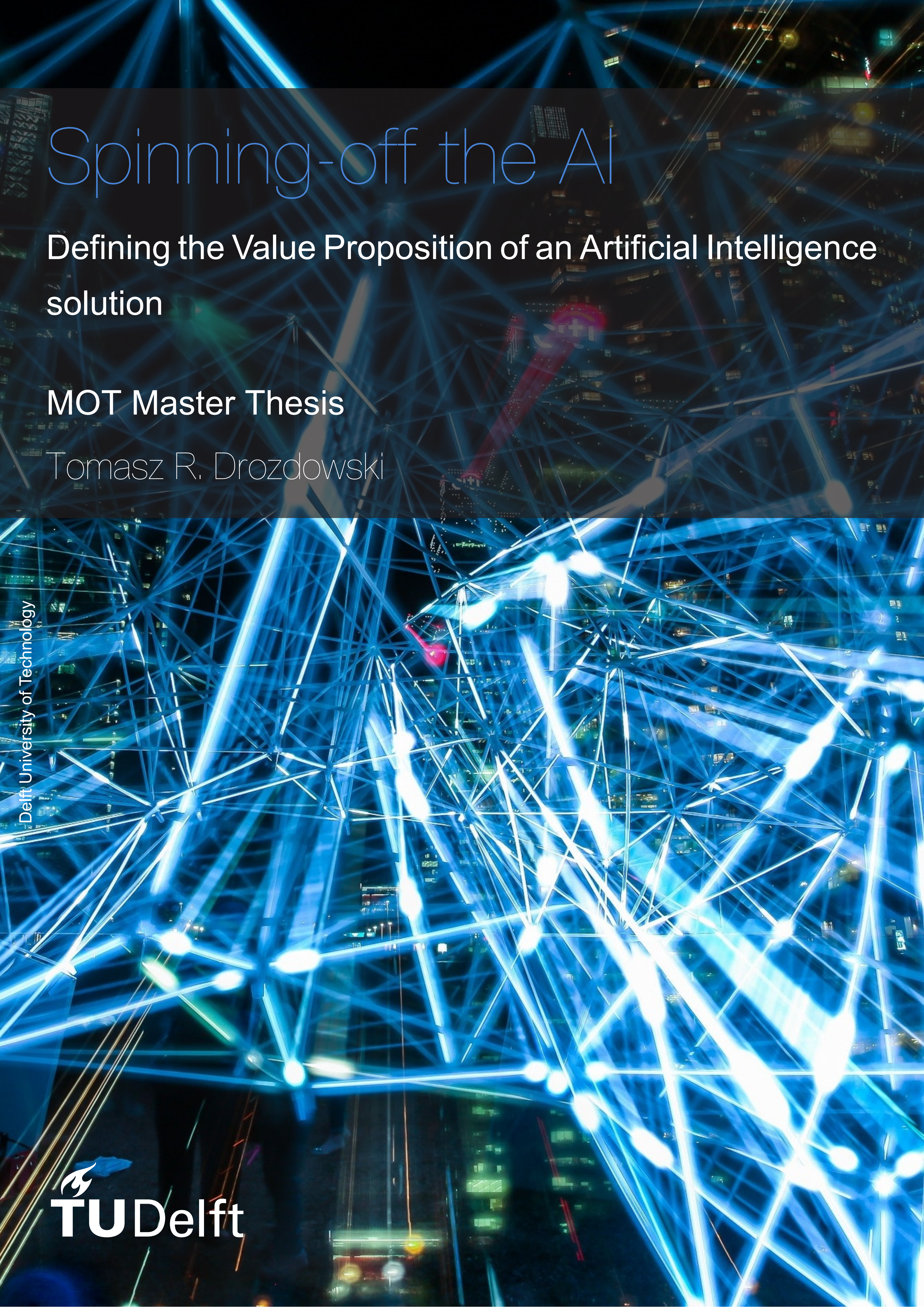

Spinning-off the AI

Defining the Value Proposition of an Artificial Intelligence solution

MOT Master Thesis

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Spinning-off the AI

Defining the Value Proposition of an Artificial Intelligence solution

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Executive summary

Artificial Intelligence technology offers computational, decision-making, and optimizing abilities that surpass every previously established traditional computation method. By being able to navigate across large amounts of data, the realized solutions learn on their own and provide results that would be unattainable with other ways. The complex nature of the AI makes the solutions difficult to define. The potential is left untapped, as the solution developers struggle to define product features that would correlate with the user needs. On the other hand, the the potential AI solution users may not be aware of the AI capabilities, possibilities of integration, and automatization of the operation processes.This creates situation, in which the potential of the AI is not used effectively, and areas that could benefit from it are not able to integrate AI systems in their operation.

This research looks at this issue from the perspective of the value proposition design process. This process assumes a definition of potential benefits and uses on the side of the developer, aligning, and communicating them with the potential users. Specifically, the Value Proposition Creation model is used, as it is a method often used by AI startups and university spinoffs. The main question this research asks is "What are the factors influencing the specific value proposition of innovative AI solutions". By answering this question, the paper hopes to establish a method for understanding the specific aspects of the AI solutions that should be taken into consideration while designing an effective value proposition and communicating it with the potential user.

To answer the research question, an in-depth look is taken at the Artificial Intelligence adoption processes. First, a literature study helps define the factors involved in the AI adoption. A conceptual model is created, which is then evaluated via a series of semi-structured interviews with AI research and development experts. By doing so, the relationships between the factors are obtained and a general impact on the adoption process is understood. This allows for a formulation of the relationship of said factors with the Value Proposition Canvas. Additionally, literature research is conducted on the value proposition frameworks, which allows for a definition of good practices in value proposition design in relation to the Artificial Intelligence solutions. The obtained frameworks are then tested in a single exploratory case

study, which looks specifically at the idea of Deep Reinforcement Learning algorithms used as a decision-making method in the context of road maintenance planning.

The research provides an overlay on the Value Proposition Canvas, obtained through the evaluation of the AI adoption process. Such approach creates a framework, which then can be used to effectively define and clarify the individual values, benefits, gains, and features of an AI product. Moreover, by providing the interrelationships between the adoption factors, understanding of the internal dependencies of factors necessary in the product development process can be obtained. The framework can be used by developers in the field of Artificial Intelligence to assess the necessary requirements of the solution, highlight the key areas that have to be researched, as well as help in communicating of the crucial solution aspects with the potential clients and users. The framework can be best used in the context of an AI startup or a university spinoff, because of its generalist approach. It assumes a fast development of a value proposition, which is necessary in the context of a Minimum Viable Product definition.

The results of the research combine the adoption processes of the AI solution and the method for their value proposition, realized with the VPC. It has been shown that the adoption factors may play a relevant role in the value definition of the potential solutions. Because the adoption models may not be used directly in the VP processes, a framework of questions has been setup for the solution developers to reflect upon during the Value Proposition Creation. Such approach is in line with the general methodology of the VPC, as it uses questions to define the relevant fields of the canvas. The goal of the research was not to modify the canvas itself, as its intrinsic agility and simplicity is the core strength. Moreover, by looking at the common practices seen in other Value Proposition frameworks, good practices have been defined for the VPC in relation specifically to the Artificial Intelligence solutions. These results have been afterwards validated in the exploratory case study for the Deep Reinforcement Leaning decision-making system in the field of road maintenance, indicating the specific steps that the solution developer must undertake and creating an example Value Proposition Canvas for this specific case.

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Introduction

Artificial Intelligence (AI) and digitalization play a key role in transforming the present-day reality (Verhoef et al., 2021). These solutions are able to seamlessly handle large quantities of data, perform fast analyses with directly visible results, as well as find answers previously unknown due to the computational complexity. Across the technical landscapes, the role of AI applications is increasing, as its precision and effectiveness in generating solutions are unmatched by standard computational techniques (Moorman, Frownfelter, Wretling, Price, & Taraman, 2020), (Balakrishnan, Chui, & Henke, 2020, November). Remarkably, Artificial Intelligence transforms the frameworks and operational methods into more adaptive and resilient ones, providing them with unprecedented capacities. With these aspects in mind, a potential for new practices, previously unreachable due to their computational complexity, is being created; the approach to solution development radically changes.

Rising interest and demand for the application of AI technologies naturally generates increasing momentum in research and development, as well as commercialization of the AI solutions. Universities and research facilities are increasingly likely to transform their high tech inventions into spin-offs. These spin-offs (or spin-outs) are a type of tech startups aiming at commercializing the raw technology by creating a marketable product. This method of academic entrepreneurship allows for business development and market verification of technological breakthroughs (Hogan & Zhou, 2010). By following the practices of startup development, universities are able to commercialize the generated knowledge, further enhancing the research and allowing for real life application. This is reflected in the growing interest in the

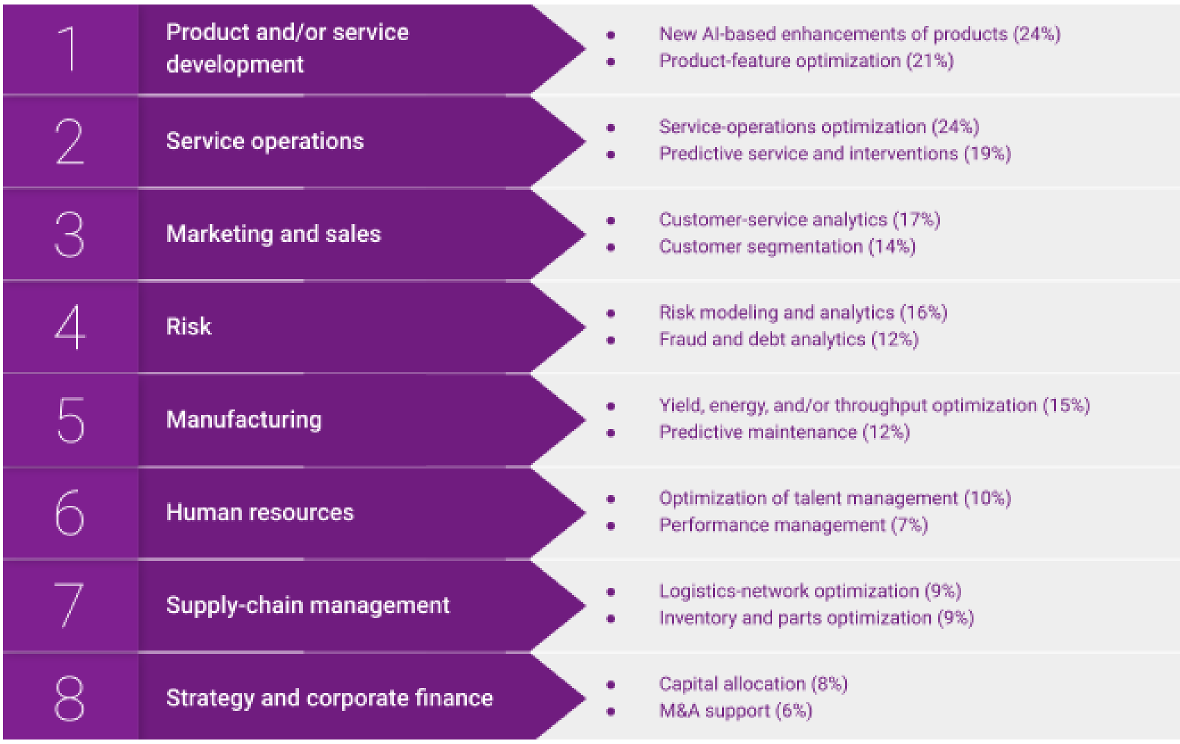

Figure 1.1: AI use cases most commonly adopted within each business function, % of respondents, as stated in the McKinsey Digital Global survey: The state of AI in 2020 (Balakrishnan, Chui, & Henke, 2020, November)

university spinoffs, methods for their developments, and realized solutions (van Burg, Romme, Gilsing, & Reymen, 2008).

What follows is a growing number of high tech spinoffs that set off on a journey of commercialization of AI products and solutions. These spinoffs are presented with unique opportunities and challenges that are not necessarily reflected by the business processes of other startups (Minshall & Wicksteed, 2005). Nonetheless, entrepreneurial methods for business development are used by the founders to create and run them. This paper looks in particular at the processes initializing the startup development and focusing of the value proposition, customer segments, and product-market fit.

1.1. Problem statement

The solutions developed by the researchers and engineers must be confronted with the requirements of the customers and the market. Outlining the added value of a specific technology is a multifaceted problem, and oftentimes undergoing rapid adjustments. Defining the value proposition (VP) is the first major step in any entrepreneurial project (Payne, Frow, Steinhoff, & Eggert, 2020). By understanding the unique aspects of the product or solution, the organization is able to orient itself in the market. Its definition affects every aspect of business development, used constructs, as well as methods of operation. Simultaneously, value proposition is the first indicator of business capability promised by the organization to the potential clients, stakeholders, and investors. In the world of startups and spinoffs, a significant portion of early operations is dedicated solely to the value proposition rationale and its refinement. Still, the notion is not conceptualized well yet; despite the needs, currently available frameworks act as guidance, a method for VP assessment (Hofmann, Oesterle, Rust, & Urbach, 2019). What is more, it seems that lack of competitive and well-defined value proposition is one of the main reasons for early startup failures (van Burg et al., 2008).

In order to better define this problem area, four main challenges are given from the perspective of the spinoff developer.

1.1.1. Value proposition for AI technologies

The genesis of value proposition comes from the product benefit framework. Traditionally, product-oriented systems followed the path of product creation, production, and selling, with intermittent steps and methods along the way (Payne et al., 2020). As the understanding of entrepreneurial methods, and market requirements evolved, a value delivery system came into play. This framework assumes the understanding of core desires, and turning them into marketable, and definable product/solution benefits. Soon as the VP frameworks became mainstream, organizations started to integrate them directly into their business models.

The value proposition defines the sets of core advantages and benefits, often unique to the given product/solution. Therefore, VP should not be understood as a list of features, or parameters. These technical aspects help define the VP, however they cannot be translated into the benefits without the consideration of the customer segments and market requirements. In the world of startups, defining VP is often the first step of any entrepreneurial activities. It precedes the beginning of search for the problem/solution fit; often the product unique benefits are revisited and readjusted at later stages.

A method often used in the startup setting for describing and visualizing the relationship between the Value Proposition and the Customer Segments is the Value Proposition Creation (VPC), usually defined with the Value Proposition Canvas (Osterwalder, 2014). This approach formulates the associations between the solution's Value Map: Gain Creators, Pain Relievers, and Product and Service Features, and the Customer's Profile: Gains, Pains, and Customer Jobs. A good fit is achieved, when the provided values match with the customer understanding.

The process allows for specific addressing of the client requirements with the benefits of the solutions, as well as highlights the essential aspects of the product. Figure 1.2 presents a standard Value Proposition Canvas.

Figure 1.2: Value Proposition Canvas - example (Osterwalder, 2014)

Specifically for artificial intelligence solutions (among other high technologies), defining the value proposition is a major challenge. When considering the VPC approach, the three elements of the Value Map must be formulated, however their identification generally proves difficult. Due to nature of high tech, oftentimes these solutions are very innovative and lack understanding of their applicability. This results in the inability of the business product developer to establish a meaningful connection between the assessed values of the solution and the corresponding needs of the customer.

The ensuing problem has consequences that impact the business development, solution provision, and general development of the technology. Without a solid value proposition, the created AI product may not correspond to the actual issues and requirements of the potential customers. Additionally, lack of uniformity and a well established goal on the product development side leads to ineffective business operations, lack of understanding, feature cannibalization, and incorrect product-market fit. It has been seen across several industries that insufficiently built value propositions for the AI products led to their dismissal and lack of technology absorption (Trivedi & Patel, 2021), (Stern, 2022). While it is easy to dismiss an unsuccessful product launching, or inability for a solution to go beyond proof-of-concept stage, studies have shown that despite being an outperforming technical solution, Artificial Intelligence products often fail to be adopted as a common method of operation (Aslam, Karjaluoto, & Varmavuo, 2021), (Stern, 2022). Therefore, it seems that looking beyond the technical feasibility and product-market fit is needed, especially for the complex and potentially revolutionary AI solutions. Aforementioned studies highlighted the aspects of data availability and protection, privacy concerns, understanding of the methods of AI operation - however, a more detailed analysis of adoption factors is necessary.

1.1.2. Customer Profile

The customer discovery is a process that explores different market segments in search for a problem/solution fit. This client search focuses on determining whether the startup's value offer meets the customer group it intends to address. Startups are known for using the Lean method for the business development, which assumes the definition of a Minimum Viable Product (MVP) (Ries, 2016). What follows is the product development oriented towards a specific customer. An approach, where the mainstream customer is served is generally not feasible because of the limited resources, manpower, and production output of a startup.

Osterwalder defines the Customer Profile in the Value Proposition Canvas as "The set of customer characteristics that you assume, observe, and verify in the market." (Osterwalder, 2014). This section of the VPC focuses on the potential benefits, obstacles, and tasks to be fulfilled with the proposed product in the given customer segment. By testing the assumptions of the MVP, the startup developer is able to demonstrate the fit of the value proposition with regards to the particular client, and adjust the developed solution as needed.

On the other hand, Eric Ries states that the customers themselves do not directly indicate what they want from the product (Ries, 2016). Through their actions or inactions, they disclose the truth. Therefore, developing hypotheses for the application of complex, high tech solutions proves difficult; the number of assumptions often exceeds the certainties. For spinoff developers this means that finding a feasible market segment, as well as understanding and testing the propositions without a clearly definable customer is overly challenging.

1.1.3. Conceptualization of technology

What combines the problem areas of ambiguous value proposition and customer profiles is the idea of technology conceptualization. It remains unclear, what the opportunities and challenges of the technology application can be, if the technology itself is still unclear (Linde, Sjödin, Parida, & Gebauer, 2021), (Margaret Taylor, 2012). Many of the ideas developed by spinoffs are undergoing major developments; the scope and goals may ultimately change. Therefore, the applicability of the product, the resulting strengths and obstacles may not be definable adequately.

There is another aspect that should be taken into consideration. Although the assumptions – both technological and business – may be correct and beneficial for a given product concept, it does not rule out the possibility that other approaches may be more effective for an early stage spinoff. Technology is therefore understood as the raw material, the building block of an innovative, marketable solution. As an example, blockchain technology, most famous for enabling cryptocurrency exchange, sees high development potential in supply chain management (Marchesi, Marchesi, Tonelli, & Lunesu, 2022). The spinoff developer is faced with the challenge of discovering a viable application by exploring the possibilities and testing hypotheses.

To better address the issue of technology conceptualization and its realizable applications, a Technology-Product-Solution model is introduced. It assumes the technology to be the material, from which a product can be crafted. Therefore, only a portion of it is used to create the technological product. Similarly, the marketable solution encloses what is actually provide to the client, as a direct response to the burning problem. Figure 1.3 presents the Technology-Product-Solution model, as a representation of their co-dependency.

Figure 1.3: Representation of the Technology-Product-Solution relationship

The technological ambiguity leads business and solution developers to a state in which they are unable to successfully and clearly define the solution needs and goals in relationship to the market requirements. AI complexity makes the product / feature / solution definitions difficult, adding a layer of complexity to the product management. A situation, where 'AI can do anything' leads to issues with actual conceptualization of the product requirements and goals. Additionally, it makes the communication of advantages with the potential market burdensome, understanding of the customer pains and needs demanding, and setting product boundaries unclear.

1.1.4. Value Proposition Creation for high tech solutions

Finally Value Proposition Creation, the common methodology of assessing the value proposition of a technical solution by university spinoff developers has to be looked upon. The main strength and benefit of using the VPC is the ability to quickly construct, assess, and communicate the solution advantages and benefits in relationship with the actual customer requirements. This in turn necessitates the method to be easy to use, uncomplicated, and developed in a LEAN approach in mind. The problem that complex high tech, or AI products impose on the VPC as a method is that they require a major change in the VP methodology (such as - adding an additional value field), which in turn kills the purpose of using the VPC itself, as - by definition - the canvas has to be quick and easy to construct.

These issues have been previously recognized; modifications of the VPC have been proposed for complex solutions (Belleflamme & Neysen, 2020), (Carter & Carter, 2020). It can be argued however that these significant canvas method modifications do not add value to the VP process itself, and in fact overcomplicate a simple method, leading to misunderstandings, ineffectiveness, and inability of value communication. For these reasons, one of the goals of this research was to leave the core - the Value Proposition Canvas - in tact, without adding any extra fields, or checks. Instead, any change to the methodology should be in line with the VPC method, i.e. asking relevant questions to assess the value fitness.

What is more, Value Proposition Creation assesses the proposed (tech) product only on the basis of the product advantages, benefits, unique gain creators, and pain relievers. The VP process does not look at solution adoption factors, which seem to be highly relevant for effective value creation (El-Haddadeh, Osmani, Hindi, & Fadlalla, 2021), (Simmonds & Bhattacherjee, 2014). This in turn creates a situation, where (1) the VPC should not be changed for sake of its efficiency and simplicity, but on the other hand (2) the adoption factors are considered strictly in the technical, and not the value domain. This paper proposes a method of reflecting upon the technological solution adoption factors, which is in line with the VPC methodology, however without any alterations to the canvas, its goals, and objectives.

1.2. Knowledge gaps

1.2.1. Assessment of the Artificial Intelligence Value Proposition

In the VPC, the value map specifies how the solution provides results and advantages that the consumer expects, such as functional usefulness, (social) benefits, and cost savings. Moreover, it states how the product proposes to lessen some of the factors that irritate or impede your consumers from completing an action.

The use of innovative technologies and methods by organizations as strategic tools for the process of decision making is not a recent practice. AI applications are able to perform tasks that required cognition, ergo typically associated with human actions. Therefore, the connection of the AI technologies usage with business strategy becomes significantly more complex in relation to other emerging innovations, as these were not subject to similar evaluations and value proposals. It becomes challenging to assess these values due to the paradox of AI perception – the same persons may have vastly different opinions on AI implementation and usefulness, depending on the particular situation (Lichtenthaler, 2019). What is more, the research has only just begun to explore the implications of AI for managers and firms (Sjödin, Parida, Palmié, & Wincent, 2021), hence empirical data for value definition of AI solutions is lacking in quality and quantity. All in all, the assessment of artificial intelligence products and its corresponding values is not trivial, and spinoff developers lack tools and frameworks for their evaluation.

1.2.2. Identification of the necessary AI features

One of the main promises of AI and other digital technologies is the reestablishment of the currently employed methods and techniques of working, allowing for creating and benefiting from new opportunities, previously unattainable to users. Therefore, as AI solutions are being introduced to the market, the business operations adapt and change. As an example, an individual framework may be responsible for monitoring, analyzing, controlling, and automating the performance of connected equipment (Sjödin et al., 2021).

By combining several functions, artificial intelligence methods are able to transform the ways that businesses operate. This presents a unique opportunity for developers and users to benefit from adaptable, tailor-made frameworks that fit within the business operation. Nonetheless, capturing the value proposition remains a challenge, as the form of products and services is often ambiguous. What stays unknown is the method for providing AI solutions to customers – combining functionalities and features. Specifically, in the face of MVP definition, identifying the most crucial attributes of the product is difficult, as judging the importance of features is often based on assumptions.

1.2.3. Lack of understanding of the AI Customer profile

In the VPC model, customer pains and gains focus on the customer issues resolvable with the solution and the resulting outcomes and specific benefits. By focusing on the potentially improvable areas, business hypotheses can be made, directly relating the product development to a specific implementation. However, by looking at the artificial intelligence solutions, it seems that many firms had failed to implement AI beyond a proof of concept stage due to issues of value creation, delivery, and capture (Sjödin et al., 2021).

Stemming from the knowledge gap of AI features identification, there seems to be a gap in understanding the customer problem areas, within which AI solutions could provide measurable and scalable opportunities. In the face of AI spinoff development, this obstacle results in the inability of gaining traction in the potential market segments and obtaining early adopters for the specific product. There is not enough knowledge about value capture for artificial intelligence solutions in businesses, hence the processes of pain, and relief identification are seemingly ineffective. This is further exemplified by the digitalization paradox, where the increasing revenues from digital services fail to deliver greater profits because of spiraling cost increases (Sjödin, Parida, Kohtamäki, & Wincent, 2020), (Gebauer, Fleisch, Lamprecht, & Wortmann, 2020, 3).

1.2.4. AI adoption and implementation in organizations

AI is considered to be a technology that has been presented as a method of replicating human decisive actions with the ability to draw conclusions via learning and self-improvement. Therefore, AI has the potential of enhancing human cognition or potentially replace human in jobs that need cognition in organizational contexts (Borges, Laurindo, Spínola, Gonçalves, & Mattos, 2021). In the VPC model, the customer jobs refer to the actions that customers undertake as their normal activities, for which the developed product may present a certain value.

It is challenging to assign, what customer jobs / tasks could benefit from the application of the artificial intelligence solutions. Research indicates that AI may not provide definite answers, but rather provide preliminary solutions (e.g., probability-based forecasts) (Sjödin et al., 2021),(Tarafdar, Beath, & Ross, 2019, 4). Therefore, human interpretation of these outputs is still needed. Such approach might result in a necessity of reshaping the business structure, adjusting task definitions and responsibilities within the unit. What remains unclear is how digital transformations affect business structures. The application of such techniques reshapes organizations – which in turn affects the basic definitions of the AI product features.

1.3. Key concepts

Artificial Intelligence (AI) refers, in its broadest sense to the simulation of human intelligence by a system or a machine (Borges et al., 2021). Other definitions also include the necessity of reasoning (Moorman et al., 2020). An AI system is therefore able to learn, think, understand the reality within which it is operating. Artificial intelligence sees potential uses wherever mimicking human thought processes is of value. Our understanding of its applicability, combining the efficiency of operation, error and risk minimization is steadily growing. Its ability to reason in big data environments makes the appropriateness of AI-based solutions compelling. Understandably, a great amount of research and development efforts go into testing and realization of such solutions. AI's decision-making capacities, paired with the relatively low costs and low fidelity of feasible applications make it a viable product that can be explored and provided by startups to a multitude of customer segments. Currently, feasibility of application is explored across the modern industries.

Customer Discovery (CD) refers to the collection of methods, actions, and frameworks used by entrepreneurs to find and integrate potential customers into their product development. CD also indicates the process of business hypotheses validation within these potential customer segments (Batova, Clark, & Card, 2016). The Lean approach of startup development is based on the concept of quick hypothesis testing with the customers, engraved in the often stated phrase *"Get out of the building"* (Ries, 2016). Compared to the Value Proposition, Customer Discovery is not a 'strictly' defined mechanism, rather it encompasses the necessary these actions that refer to said process.

Deep Reinforcement Learning (DRL) is an innovative machine learning method that helps define the optimal sequences of actions, further referred to as policy maps. In its core, it combines the model based engineering with the data-driven approach (Botvinick et al., 2019). By exploring the decision combinations, DRL provides an action strategy, a method comparable with the knowledge of chess – how to act and when. It may help the decision makers find the optimal decision pathways that previously were unattainable via conventional modelling methods. Deep Reinforcement Learning can be effectively implemented in the extremely complex network environments, where normal cognitive operations are inefficient. In the recent years, its validity has been confirmed in complex strategic planning in games, both physical and virtual (Mnih et al., 2013), as well as in the field of robotics (Nguyen & La, 2019). Researchers are actively studying its potential usage in autonomous vehicles, infrastructure maintenance, IT, etc. (Kiran et al., 2021). DRL, being type of Deep Learning, is shown on the AI subset classification in figure 2.1.

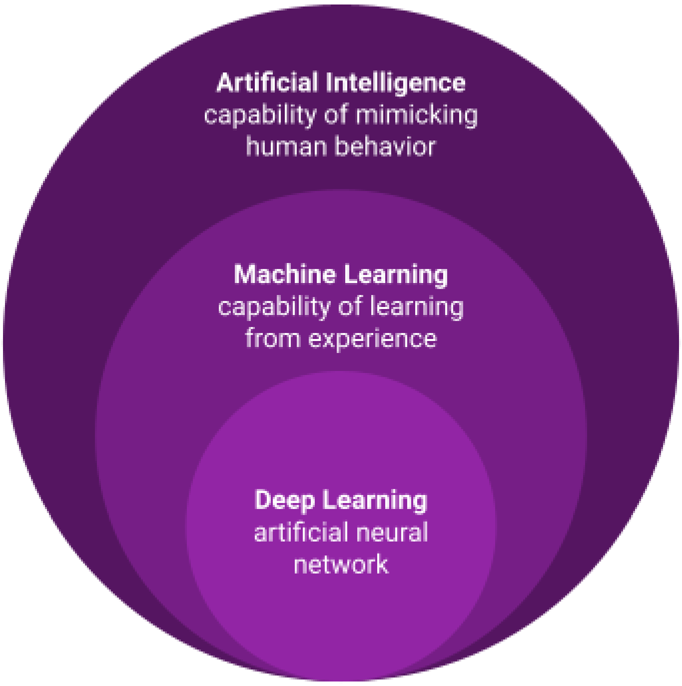

Figure 1.4: Artificial Intelligence, Machine Learning, and Deep Learning - subset classification (Borges, Laurindo, Spínola, Gonçalves, & Mattos, 2021)

Lean Startup (LS) is a business development method, employing the rapid Build-Measure-Learn technique (Ries, 2016). It combines turning ideas into products as quickly as possible, minimizing development and sunk costs. In its core, it assumes fast product definition (Build), testing it in potential customer segments (Measure), and reevaluating the initial proposition (Learn). In this way, the developers are able to adapt the solution to the paying customer, aligning it with the needs and requirements. Moreover, it negates the unnecessary costs of development of a not validated idea. LS draws heavily from methods for value proposition, while defining the Minimal Viable Product.

Minimal Viable Business Model (MVBM) refers to practices of *"designing multidimensional customer experiments and tests revolving around the notion of value"* (Ghezzi, 2020). Similarly to an MVP, MVBM assumes the definition and testing of business hypothesis, consistent with the Lean approach. By building initial business models and assessing them through real life cases, entrepreneurs are able to learn and adapt their assumptions with feedback information generated through market experiences. These models allow for validation of concepts that are intrinsic to the Value Proposition processes and involve the potential customers in the conceptualization of both the product and business design.

Minimal Viable Product (MVP) - Eric Ries defines the Minimum Viable Product as *"version of a new product which allows a team to collect the maximum amount of validated learning about customers with the least effort"* (Ries, 2016). In the context of a Lean Startup, this necessitates the developers to ideate and test the proposed solution with the potential customers, while focusing on its true, core value. It also allows verification of the product assumptions with real life opportunities and obstacles, therefore not operating in the vacuum of an isolated business case scenario. The process of validation relies on testing of the business hypotheses, which rely on the proposed value for the given product.

University Spinoff Is a company established for commercializing of university knowledge, often founded as a continuation of a research project (Hogan & Zhou, 2010). Spinoffs take advantage of the university's intellectual property, creating marketable product and engaging in business activities. This brings revenue to the academic, as well as promotes the knowledge and research that is being conducted. Their development is frequently based on the principles of a Lean Startup, therefore rapid ideation and business hypothesis testing is a common occurrence. Nonetheless, spinoff development methods tend to differ in the stage of ideation, as their products are more bound by the academic IP's capabilities. Hence, their evolution and progression differs from a regular startup, yet is not as well analyzed and described in the literature.

Value Proposition is a finite set of the core benefits that a particular solution, or method offers to the party interested in its application (Payne et al., 2020), (Osterwalder, 2014). It relies on the definition of unique advantages, which are significant to the particular situation of the user. Therefore, the value proposition encompasses the technical abilities of the proposed solution, and defines their specific qualities. It should not be understood as a list of features, or parameters. In the startup context, a value proposition is what differentiates the product in the given customer segment from the competing solutions. VP serves both as the foundation and the reflection of the Minimum Viable Product.

Value Proposition Creation (VPC) is a method for designing and testing products in the startup environment, based on the iterative approach of defining a specific value proposition and searching for what the potential customer may require (Osterwalder, 2014). The Value Proposition Canvas is composed of two main sections: Customer Profile, used for clarifying the user needs, and the Value Map, which translates product attributes into potential values. We say that “fit” is achieved, when the customer needs are accounted for by the product values. The model operates on the basis of a MVP, therefore a rapid Build-Measure-Learn technique is applied there as well. The main strength of the model is the continuous improvement of the product based on the feedback from the customers. It forces the developers to analyze and understand what is truly required, and where the burning problems are in the market segment.

2

Research methodology

2.1. Research problem

The main focus of this thesis is to enable spinoff developers to create more effective, custom AI solutions that respond to the needs of their customer segments. The research focuses specifically on the implementation of scalable Artificial Intelligence products for specific purposes. It seems that the potential for the improvement of operations, and opportunities resulting from the application of AI in such environments is high. Therefore creating and capturing value via high tech solutions is beneficial and must be well understood.

Moreover, high tech spinoff development differs greatly from regular startups. Based on the knowledge gaps, the obstacles in the Value Proposition Creation process are significant and may interfere with the establishment of successful spinoffs. Both, on the side of Value Map and Customer Profile, the methods for defining, testing, and adapting the business propositions lack proper definition. Without the possibility of clear value proposition, spinoffs are often unable to propose a MVP in a specific customer segment, in reality blocking their way for any further development. Aside of not being able to market a product, such situation generally results in the inability of acquiring initial funding.

Therefore, effective VPC process is crucial, especially in the early stages of startup operations. By becoming product-oriented, startups are able to systematically review and adjust their course of action based on the client needs. The constant reiteration of product-market fit ensures that the problems are addressed and values captured. However, the discrepancy in the VPC processes of standard startups and high tech university spinoffs is significant. This research expects to enable a more effective approach for AI value proposition creation in spinoffs. Moreover, the paper provides a better understanding of the opportunities and challenges of AI implementation in the business setting and its subsequent translation into product features.

2.2. Research objective

Goal of the thesis is to address the issues of the Value Proposition Creation and provide a framework that is more beneficial for the AI Value Proposition process. This assumes using the VPC practices and defining necessary steps in line with the VPC method. Additionally, grounding of the business practices in relevant scientific literature is crucial. The research looks distinctively at the Value Map and Customer Profile. By considering the individual aspects that influence the particular areas of the VPC model, the research addresses their deficiencies in face of a AI spinoff development. What is more, it proposes specific points for improvement of these areas, enabling a better connection of the product-customer fit.

By addressing the problem areas, the research aims to permeate the knowledge gaps and propose additions to the VPC framework as a method for value proposition in AI spinoffs. It reflects on the VPC literature and factors that determine the usefulness of the model, as well as evaluates the findings via a qualitative analysis. To improve the research relevance, particular look is taken at the field of AI predictive maintenance and the case for its usability in the maintenance decision making of physical assets.

2.3. Research question

The research question is stated as:

“What are the factors influencing the specific value proposition of innovative AI solutions.”

The question focuses on the notions that affect the particular areas of the Value Proposition Creation model. Understanding the factors that are involved in the value proposition process may help in improving the VPC model for the specific application of AI spinoffs. Addressing the individual aspects of the model is necessary for obtaining a holistic view on the process and understanding how the intrinsic values of the artificial intelligence technologies reflect on the product value definitions and customer fit.

Furthermore, it aims to form a relationship between the technical and market aspects of artificial intelligence solutions. These elements do not exist in separate domains, hence bridging the technical abilities with actual customer needs becomes essential for effective product definition. As value proposition works in the product domain, a method for translating the benefits and opportunities from the technical and market areas is needed.

2.4. Research sub-questions

In order to answer and guide the main research question, the following sub-questions are stated:

1. **What aspects of the Artificial Intelligence technology are responsible for its adoption?**

By considering both the technical and market aspects of AI solutions, the aim is to define the points favoring the use of AI by the business customers. Moreover, by looking at potential opportunities and challenges, it becomes possible to define a set of factors involved in the solution adoption. It must be understood, what opportunities are created and what obstacles can be overcome. The customer gains must be specific, practical, and measurable. What is more, considering the model for the Minimum Viable Product, they have to respond to a specific problem that is seen within the customer segment.

2. **How to assess the benefits and opportunities of an AI solution in face of the technical abilities of the Artificial Intelligence technology?**

Through looking at the innovative features of the AI, it becomes possible to highlight the possible advantages and benefits.Looking at the possibilities that a novel solution might propose must go hand in hand with the analysis of the client actual needs. Aside from addressing a burning problem, the solution must fit within the structure and methodology of the client operation. Therefore, the problems that the customer has must be viewed through the lens of technical capacity of the proposed solution. A method for the assessment of the customer's needs is needed for the development of realistic and feasible solutions.

3. **How to create a meaningful connection between the user need and technical ability of the AI system?**

One of the most significant challenges is establishing the relationship between the customer needs and methods of operation and the proposed AI solution. Especially in the early stages of the spinoff development, it must be realized that the MVP may not exist in the vacuum and that is has to implemented within the business customer structure. Literature points to the fact that because of the inability to consider specific realization of the solution within the organization framework, many of the AI solutions do not go past the point of proof of concept (Sjödin et al., 2021). Therefore, this connection between customer and value proposition must be defined and created.

4. **What are the specific aspects of Artificial Intelligence value proposition that make it unique and challenging to design?**

Successful Minimal Viable Product development must consider the features that are essential to the client. Understanding the value proposition process is therefore crucial for an effective value capture of the potential customer. However, due to the innovative and complex nature of the AI products, the methods for designing a coherent value proposition are ineffectual.Additionally, the proposed products and services that an AI spinoff offers within the solution have to be aligned with the customer requirements and their needs. Specifically for AI, the range of methods, in which value can be delivered (i.e. software, framework, service, or a combination of those) is large. Hence, by determining the advantages of each method of value provision, the spinoff might be able to create a better, more feasible, and scalable product.

Table 2.1 presents the methods used to answer the particular sub-questions of this research.

2.5. Research approach

In order to answer the research sub-question exploratory research methods are used. Determining the factors that influence the value proposition for Artificial Intelligence solutions requires investigating a nontrivial problem that is not yet clearly defined. Therefore, the thesis is conducted in a form of a qualitative study with an inductive approach for theory generation. These developed theories and insights are then used to form an improved VPC model, specifically for the AI-based solutions. The qualitative method helps to comprehend the fundamental causes impacting the Value Proposition Creation model from the perspective of artificial intelligence development. It is reflected in the literature study and desk research approach, as well

Table 2.1: Methods for answering individual research sub-questions

01	What aspects of the Artificial Intelligence technology are responsible for its adoption?	• Literature research • Desk research
02	How to assess the benefits and opportunities of an AI solution in face of the technical abilities of the Artificial Intelligence technology?	• Literature research • Desk research • Semi-structured interviews
03	How to create a meaningful connection between the user need and technical ability of the AI system?	• Semi-structured interviews • Exploratory case study
04	What are the specific aspects of Artificial Intelligence value proposition that make it unique and challenging to design?	• Literature research • Semi-structured interviews • Case study

as in the conducted semi-structured interviews.

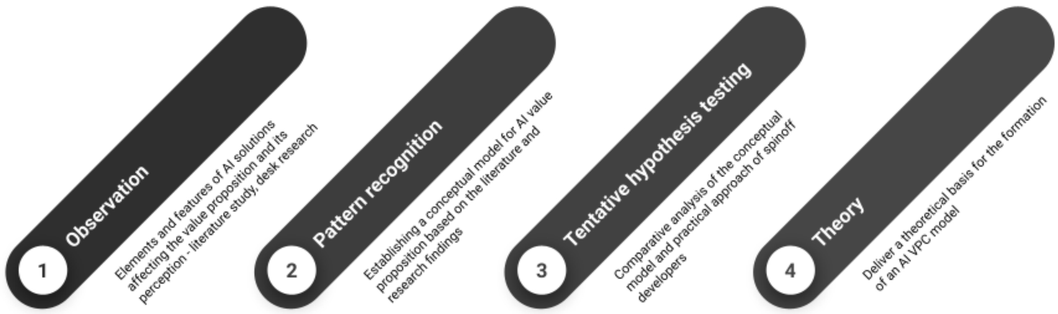

Figure 2.1: Inductive approach as a basis for theory building in the research

The first step of the research involves the identification and definition of the factors that influence the process of adoption of AI-based products. These are generated primarily from the literature review and desk research. During the literature study, the Value Proposition Creation model is also evaluated, as well as common Value Proposition practices are given. A conceptual model is formed, which shows the relationship between the factors obtained from the literature and the adoption of AI solutions. Afterwards, using the principles of empirical approach, semi structured expert interviews are conducted with AI research and developers. They are used to evaluate the adoption model and help find the impact that adoption has on the AI's value proposition. These insights are then used in the context of the Value Proposition Creation model in regards to artificial intelligence solutions. Based on these findings, an improved version of the VPC model is constructed, specifically for the defining of the value of AI solutions. This improved model is then used in a single case study to test the compatibility and draw conclusions. Figure 3.4 presents the research flow-chart, designating the individual steps of this thesis.

2.5.1. Literature review

The literature analysis is used throughout the thesis report to provide valuable insights into the researched notions. First, research papers and field specific literature is studied in order to help define the adoption factors, which can be seen in the adoption processes of Artificial Intelligence solutions. Specific strengths and opportunities, as well as obstacles are studied to gain an overview of how the AI products behave. In-depth understanding of these facilitating and obstructing factors is necessary, if we want to define a value proposition of an AI product. This is because a well-defined VP takes into consideration the ways, in which customers use the products, why they use it, and how.

Furthermore, literature analysis is used to help evaluate the Value Proposition methodology, especially from the perspective of AI. Scholars and business developers use many different methods for the value proposition design; VPC is only one of them. Therefore it is necessary to uncover the patterns of use, the strong and weak sides of different VP frameworks. By doing so, the Value Proposition Creation method can be better understood and adapted specifically for the AI applications. The VPC framework is also researched, the particular segments of the VPC are looked at individually. Literature study is also done specifically for the exploratory case study to show the relevance of road infrastructure innovation, promises of Deep Reinforcement Learning algorithms, challenges of road maintenance, and AI application in the decision-making setting.

2.5.2. Expert interviews

To validate the findings of the literature study, and gain additional insights into the specifics of Artificial Intelligence applications, a series of expert interviews are performed. First, semi-structured interviews are performed with experts in the field of Artificial Intelligence research and development. The experts have been picked from multiple fields of AI application in order to gain rich understanding of the AI adoption notions. During the interviews, the experts were

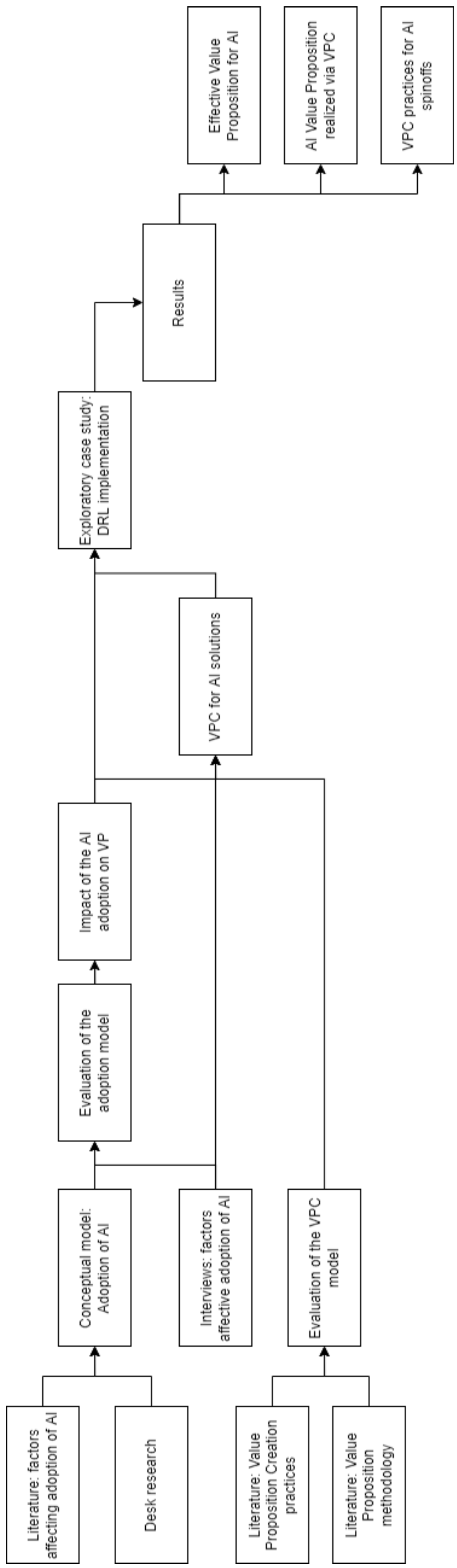

Figure 2.2: Thesis research flowchart

asked a series of questions relevant to the conceptual model for AI adoption and the value proposition for AI solutions. The semi-structured nature of the interviews allowed for certain detours, and questions into the particularities seen in the person's field of expertise. The general structure has been prepared ahead of the interviews, allowing for keeping track of the relevant topics. Additionally, all the interview participants were provided with a confidentiality agreement.

2.5.3. Exploratory case study

Moreover, an exploratory single case study is carried out in this thesis research. A case study is defined as "An empirical inquiry that investigates a contemporary phenomenon within its real-life context, especially when the boundaries between phenomenon and context are not clearly evident…[and] relies on multiple sources of evidence" (Yin, 2012). In the context of this research, a case study allows for investigation and evaluation of the possible adoption of Deep Reinforcement Learning algorithm as a decision-making tool in the field of road maintenance. Because of the specificity of this domain, it becomes possible to analyze the previously made assumptions of the AI systems adoption and value proposition. In the case study, a literature study is conducted to create a knowledge base and look for possible trends and connections with the previously obtained knowledge. Afterwards, the data is triangulated by using expert interviews. The participants for the interviews in the case study are AI developers, specializing in civil engineering, business developers, innovation manager, and an R&D expert in the field of road innovation and maintenance. The case study is finalized with a VPC made for this specific AI application.

2.6. Research relevance

This research attempts to combine a technological solution adoption framework that has been based on an extensive literature study and empirical research, with a value proposition process, described using the Value Proposition Canvas. Artificial Intelligence products, given their technological complexity, are known for their difficult assessment and understanding of applicability, value delivery, and solution feasibility. Therefore it is assumed that by looking at the potential challenges and obstacles in the adoption process, the product developers might be able to mitigate certain issues already in the value proposition process. Moreover, this approach of understanding the value proposition with the use of the solution adoption factors may influence the definition of the particular values, resulting in a more specific, realistic, and need-based benefit definition

The research aims to articulate the factors involved in the creation of the value proposition for AI-based solutions. Recently, interest in general artificial intelligence, being on par with human abilities has been increasing. These types of solutions combine multiple operational aspects, and by doing so are able to act comparably to human competence. However, development of artificial superintelligence is on the rise, as demonstrated by the latest achievements in the field of (Moorman et al., 2020), depicted in figure 2.3. Such accomplishments present us for the first time with the opportunities of surpassing our own abilities in understanding, thinking, and learning. Therefore, our understanding of the benefits of such solutions, potential gains, and requirements must progress.

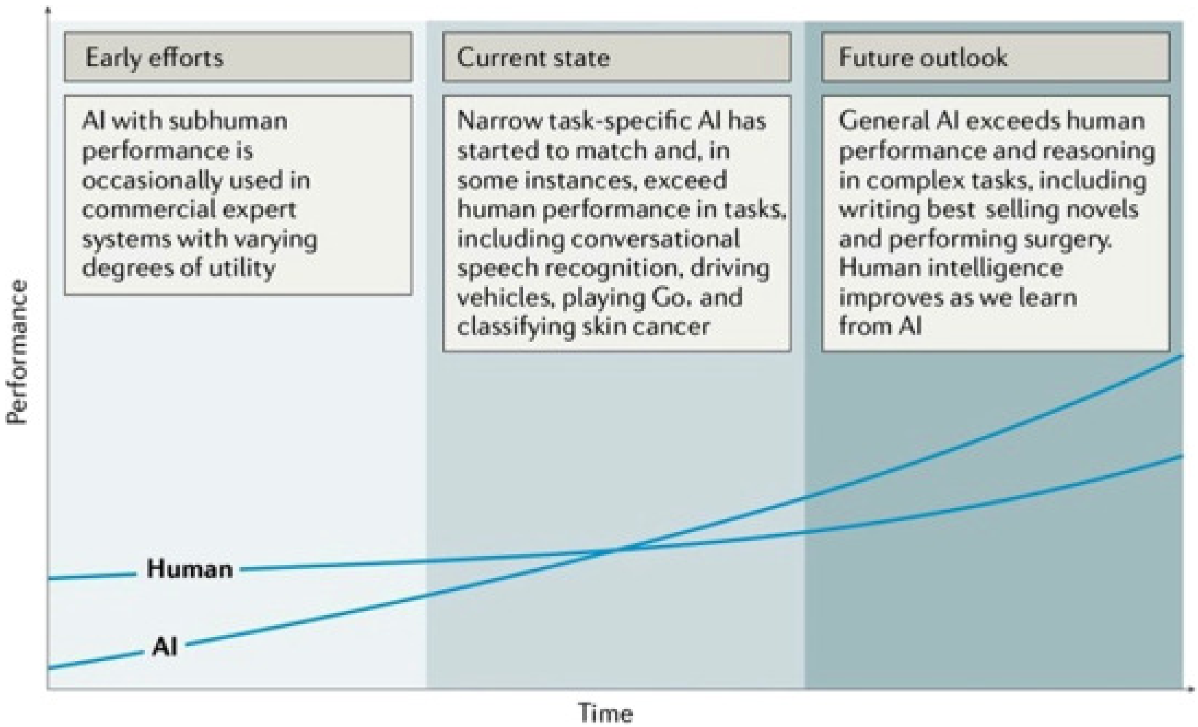

Figure 2.3: AI versus human performance (Moorman, Frownfelter, Wretling, Price, & Taraman, 2020)

From the perspective of university project spin-offs, due to their startup characteristics, their focus on the Minimal Viable Product must be met with a solid comprehension of the value proposition. Considering the fact that the novelty of the proposed AI-based products hinders their ability to specify the benefits and opportunities, the spinoff developers are unable to propose reliable solutions to the potential customers. As the interest in both AI products and university spin-offs as a method for their delivery increases, dependable methods for their evaluation are needed.

3

Literature review

The literature review of the thesis consists of three main aspects. First, the origins and development of Artificial Intelligence solutions are examined, with a more detailed exploration of the promises and challenges of Deep Reinforcement Learning (DRL) applications. Afterwards, the Value Proposition Creation model is considered; its process is analysed as well as in depth look is taken at the specific methodologies of Value Proposition and Customer Discovery, which are the two integral parts of the VPC method. In this way, a thorough analysis of the process, its strengths and weaknesses is obtained. Finally, factors influencing the adoption of Artificial Intelligence solutions are derived and examined. Solution adoption is considered to be the key entrepreneurial goal, which de facto leads to financial gains and competitive advantage; value creation and capture are strictly dependent on the adoptability and integration of the product (Osterwalder, 2014), (Sjödin, Parida, Jovanovic, & Visnjic, 2020).

3.1. Artificial Intelligence

3.1.1. Origins and current developments of AI technologies

Origins of the Artificial Intelligence can be traced back to the developments of machine intelligence, specifically in the fields of cryptology. Alan Turing electro-mechanical computing device, which's developments have been based on the findings of Rejewski, Zygalski, and Różycki (Rejewski, 1980)– is considered to be the first programmable machine that achieved computational powers vastly beyond human capabilities (Copeland & Proudfoot, 2007). Turning's later works and fascination by the idea of building an artificial brain led to further developments of what has been called intelligent machinery – early computers and memory storing devices. This has directly translated to the birth of Artificial Intelligence, in the form of heuristic algorithms, capable of methodical learning, i.e. strategizing in chess playing (Chang, 2020b).

There are several ways of categorizing Artificial Intelligence. For example, it can be subdivided into three types: analytical, human-inspired, and humanized AI (Cannataro, Guzzi, Agapito, Zucco, & Milano, 2022). This method highlights, generally speaking, the use case, or applicability of the technology. Another way is by establishing the level of cognitive evolution – narrow, general, and super intelligence (Chang, 2020a), (Borges et al., 2021). These refer to the generally understood performance of the AI system, ranging from subhuman levels of cognition, on par, and those that go beyond our capabilities. Subsequently, several subsets of Artificial Intelligence can be recognized (Chang, 2020a), (Muthukrishnan et al., 2020). Mostly recognizable are Machine Learning (ML), combining the different levels of (non-)supervised and deep learning, with its own subcategory of Deep Learning, which relies on neural networks for data processing.

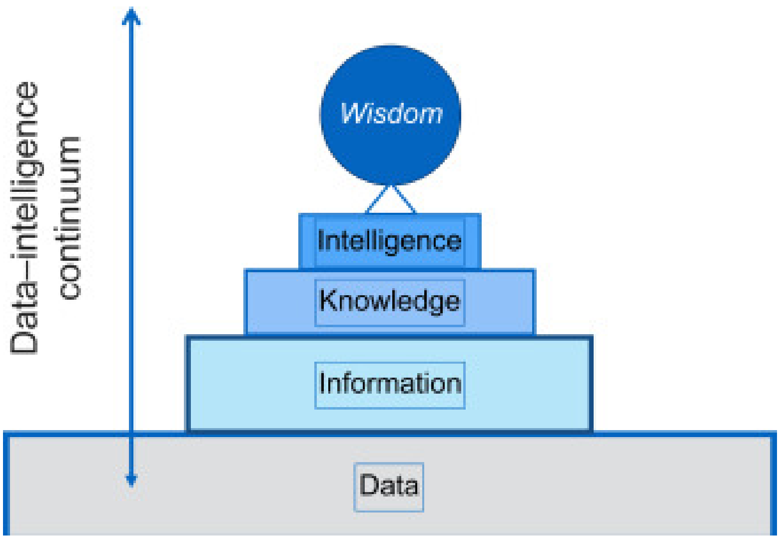

Figure 3.1: The data–intelligence continuum, adopted from (Chang, 2020a). Note the differentiation between wisdom and intelligence, as well as intelligence and knowledge.

What differentiates the Artificial Intelligence from other forms of computing is its ability to obtain, comprehend, and apply knowledge in the form of distilled contextual data (Chang, 2020a). Moreover, AI is able to use that knowledge in the pursuit of its preliminary goals. However, another crucial distinction must be made. Intelligence – including the artificial one, created by humans – significantly differs from wisdom. The former is defined, in the psychological meaning, as a way of conceptualization, method for abstraction from reality, which, as a construct, serves a purpose for functioning, adapting, and thinking within the domain one is located (Clayton, 1983). Wisdom refers to the understanding human nature; thinking in a sense of emotional, empathetic manner. It carries moral presuppositions, manners and ways for dealing with the reality. Therefore, in the sense of AI, this distinction must be highlighted, as the technology does not poses wisdom, not is able to make sound moral judgements on its own. Figure (3.1) presents the data intelligence continuum, in a form of a hierarchy.

The milestones of modern AI capacities have been set and achieved the Deep Blue (IBM) development team, constructing a chess-playing program that defeated the chess world champion (Hodson, 2019), (Muthukrishnan et al., 2020), and afterwards by DeepMind, a self-learning algorithm presenting superhuman abilities in multiple complex games. Research, development, and application of AI continues to steadily grow (Balakrishnan et al., 2020, November). The adoption of Artificial Intelligence solutions increased by 70% in the last five years (Ghosh, Daugherty, Wilson, & Burden, 2019). AI offers solutions of unmatched potential, surpassing the human capacitive and reasoning abilities. Its impact can be seen across the industries, with actors more willingly implementing them. AI capabilities is no longer bound by hardware limitations, due to their steady improvements in recent times (Muthukrishnan et al., 2020). Therefore, vast numbers of businesses are able to incorporate them into their methods of operation. Recently, Deep Reinforcement Learning techniques have gained significant attention, specifically for its ability of sequential decision-making with uncertainty quantification and optimization. In the recent years, its validity has been confirmed in complex strategic planning in games, both physical and virtual (Mnih et al., 2013), as well as in the field of robotics (Nguyen & La, 2019). Researchers are actively studying its potential usage in autonomous vehicles, infrastructure maintenance, IT, etc. (Kiran et al., 2021).

3.1.2. Deep Reinforcement Learning (DRL) - promises and challenges

It has been shown that the technology can deal with large data sets, and find optimal problem solution pathways (Richbourg, 2018). What is more, the industrial applicability is at high level. As a matter of fact, a vast portion of the articles deals with the application of DRL algorithms in the industrial setting. It has been stated however that – like any other technology – Deep Reinforcement Learning application comes with drawbacks. There are several prerequisites for the applicability of the algorithm. A large amount of uniform data is needed, as well as a good understanding of the network behaviors (El Bouchefry & de Souza, 2020), (Richbourg, 2018). Predictive models have to be setup in order for the algorithm to define the optimal policy pathway. With at that being said, what sets this approach apart from other technologies is a low cost of implementation of the actual algorithms and the model's ability to self-improve, as more and more analyses are made.

Furthermore, the applicability of this technology was analyzed from the perspective of the decision makers. The policy pathways can indeed be used by the policy makers to optimize maintenance planning and execution (Huang, Chang, & Arinez, 2020), (Marović, Androjić, Jajac, & Hanak, 2018). With a more effective planning procedures, in addition to a clearer understating of alternative outcomes, budget waste may be prevented (Darvishvand & Latifi, 2021). The literature also points to significant improvements of other aspects relevant to the decision makers – optimal time allocation, reduction of emissions, more effective system performance (Andriotis & Papakonstantinou, 2018). Still, implementation of such algorithm in a rigid decision setting may be a challenge, as it might have a considerable impact on the operation procedures, definition of responsibility, and execution.

Subsequently, the specific application of the DRL algorithm in the road maintenance setting was studied (Han, Ma, & Chen, 2021). Research presented 90% accuracy in the decision making process for pavement inspection and maintenance, as well as a 4.35% higher action accuracy and 75% reduction computation time, compared to the state of the art method (Han, Ma, Xu, Chen, & Huang, 2020). Furthermore, the proposed algorithms allow for definition of long term maintenance planning (up to 20 years) (Darvishvand & Latifi, 2021), which may be further improved based on the user input (Andriotis & Papakonstantinou, 2020). DRL algorithms show promising results in the predicative maintenance scenarios, should the input data be well organized and provided (Marović et al., 2018).

The research paper of Han et al. (Han et al., 2021) provides an example of implementation of reinforcement learning algorithms in the field of pavement maintenance. They also list the advantages drawbacks of the commonly found operational, metheuristic, and AI decision making solutions in relation to physical asset maintenance. Specifically for the artificial intelligence, they list the degree of precision as its main strength. Nonetheless, the provision of clear, orderly data and predictive models is a definite requirement, as confirmed in the AiDAPT article on DRL (Andriotis & Papakonstantinou, 2020). In their article, Harvey & Gowda defined several regulatory issues and challenges that arise during the implementation of artificial intelligence systems. It can be seen that in other fields, where AI has been previously implemented on a certain scale, the risks regarding data security, liability, and internal operations remain unsolved (Harvey & Gowda, 2021).

Zuiderwijk et al. presents a systematic literature review on the challenges and significance of AI use in the field of governance (Zuiderwijk, Chen, & Salem, 2021). They highlight the necessity of AI adoption, nonetheless the paper raises the concern that the adoption rates in the governance bodies has been lacking. This literature review goes into great detail on potential benefits and challenges that were seen in the cases of AI adoption by decision-making bodies. Evaluating, confirming, and addressing these issues seems vital during the possible adoption of DRL algorithms.

Similarly, the article by Galaz et al. confirms the propriety of the risks and challenges, and further delineates systemic risks that were seen in the AI adoption in several industrial fields (Galaz et al., 2021). Another article assessing the AI in the era of Big Data highlights (among others) the challenge planning scope definition (Duan, Edwards, & Dwivedi, 2019). An important issue is the possible lack of trust of the authorities in the innovative solutions (Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2021), as well as the necessity of reforming the decision-making departments, including training and team re-adaptations. Finally, the necessity of evaluating and measuring the benefits, compared to traditional decision-making methods is brought up (Sharma, Luthra, Joshi, & Kumar, 2021).

Harvesting the potential of DRL implementation seems to be a challenge not only from the technical perspective – but also (if not primarily) from the side of implementation within the decision-making body. Despite very specific conclusions and approach recommendations, current literature lacks evidence-based methodology for a step-by-step implementation of AI in the maintenance planning. This was to be expected, considering the fact that our knowledge and expertise in the field of artificial intelligence is young and lacking. It can be however concluded that the transition pathway for the DRL must be made based on evaluations of literature, case studies, and analysis of opportunities and challenges seen in other AI applications.

3.2. Value Proposition Creation

3.2.1. Process overview

Value Proposition Creation is considered to be a visual method for representation of the key elements of product Value Proposition and the corresponding Customer Segment attributes (Osterwalder, 2014). It is used to present, discuss, and test the product assumptions in order to create a problem/solution fit. The canvas is symmetrical, as the customer requirements are corresponding to the specific aspects of the proposed solution. Business and product developers are hence able to rapidly test new ideas for their overall integrity, incorporate new product assumptions and customer feedback.

The VPC is not however a deterministic process. In its core, it should be considered as a method for verification, consolidation of the findings on both sides – product development and market research. What constitutes the 'fit' is not empirically verifiable directly from the model itself. VPC provides the business developers with specific fields to be filled out for the idea representation. Nonetheless the processes that guard the data acquisition for the distinct fields of the VPC are vast. The canvas provides an opportunity for the allocation of this information by asking the developer specific questions about potential customer segment, or product's proposed value.

What is more, the VPC method assumes a Likert-like value importance rating. This forces the solution developer to qualitatively highlight and prioritize certain aspects that seem crucial to the solution development. Afterwards, by connecting each item on the board, respective to the severity, product/customer fit is obtained. The developers are able to quickly adjust the canvas based on customer feedback, as well as the technical capabilities of the solution. Moreover, the highlighting of the vital aspects and values is critical in prototyping and the definition of a Minimum Viable Product (E. Johnson, 2012).

The Value Proposition Creation has proven its usefulness by being a simple, yet effective method for the assessment of the solution values, communicating them both internally and externally, as well as promoting a method of thinking about the solution not only as a sum of its parts, but rather their impact and relevance in the customer's operation. For this reason, the Canvas does not have a a strict method for the assessment of the technical aspects of a product - the VPC asks questions on how these aspects influence the perception of the product itself. This may in turn lead to a situation, where some of the technical aspects remain unnoticed in the product development. As an example - by studying the sample questions that the method asks for the verification of the values (Appendix: C,D), none of them refer to the user's ability of adopting the solution. The efficiency of the VPC is proven mostly by understandable, easy-to-define solutions proposed by startups, that can be quickly built and tested in the real environment.

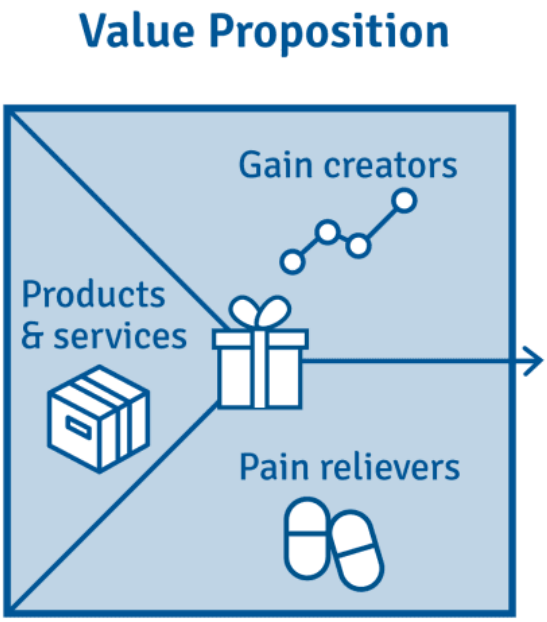

Figure 3.2: Value Proposition map of the Value Proposition Canvas; adapted from (Osterwalder, 2014)

3.2.2. Value Proposition within the VPC model

1. **Gain Creators** These values of the product explain how the solution or the services brings about gains, benefits and improvements for customers. They specifically lay out what is planned to achieve the necessary results and advantages that your consumer anticipates. Therefore, these aspects include as practical utility, social advancements, improved operation, and financial savings.

2. **Pain Relievers** This category of values refers to the ways, in which the products may ease certain client difficulties, struggles, or resolve issues. They specifically describe how the product or service plans to remove or address the annoyances that the customers experiences in their operations.

3. **Products & Services** In this subgroup, the developers list the services the solution provides. It combines the elements of the solution that the value proposition depends on. They assists and enable the clients in meeting their fundamental requirements or in completing tasks. It is important to recognize that the Products & Services only provide their value when they are related to a certain consumer group and the tasks, challenges, and benefits they experience.

3.2.3. Customer Profile within the VPC model

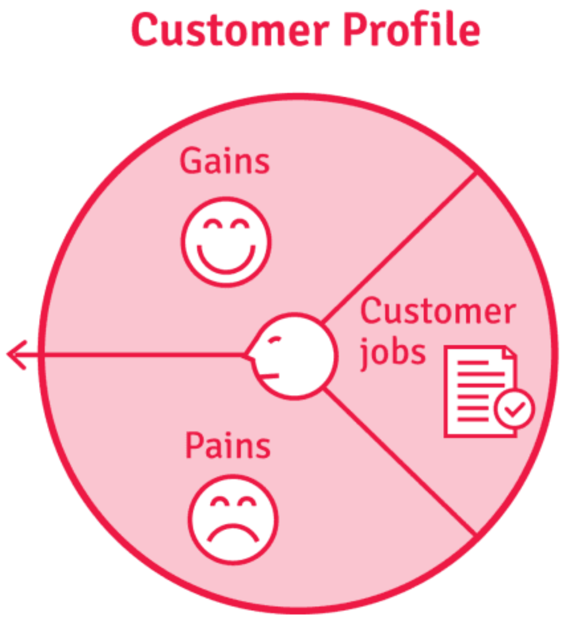

Figure 3.3: Customer Profile map of the Value Proposition Canvas; adapted from (Osterwalder, 2014)

1. **Gains** The customer gains are the results of the solution that the customer desires and wants. Some of these gains may be unexpected (i.e. beyond their expectations), but the vast number should be required, expected, and desired. Gains include economic savings, social benefits, good feelings, and functional utility that is realized with the product.

2. **Pains** Any aspect of operation that irritates the potential client before, during, or after they attempt to complete a task – as well as simply keeping them from completing one – is referred to as a pain. Pains may refer to dangers, or possible negative results, associated with doing a task incorrectly or not at all. In the context of the product or a service, they include undesired outcomes and problems, obstacles, and risks.

3. **Customer Jobs** This group of factors are the tasks that the potential client attempts to achieve. A customer's work may consist of the duties they are attempting to carry out and finish, the issues they are attempting to resolve, or the wants they are attempting to fulfill. When examining the customer jobs, it is crucial to consider the viewpoint of the consumer. What may seem to be significant from the provider perspective might not necessarily be what consumers are actually attempting to accomplish.

3.3. Value Proposition methodologies

By looking at the methods for Value Proposition, we are able to understand the processes in which business developers engage in order to define, articulate, select, and evaluate the specific values of a proposed product (Nenonen, Storbacka, Sklyar, Frow, & Payne, 2020). The VPC then allows for the collection and representation of these values within the Value Map: Gain Creators, Pain Relievers, and Products & Services. It should be remembered that Osterwalder argues that the value definition and customer segment research are not separate, or finite processes. Rather, they complement and interact with each other, providing a more general overview on the state of the problem/solution search.

Throughout the years, the idea of an effective Value Proposition framework as a method for distillation, evaluation, and presentation of specific product / service values went through several phases of evolution. The frameworks, constructed for both for consulting / business applications, as well as academic purposes, were expanded and developed based on our understanding of the applicability of solutions, value communication, and capture.

Before the conception of value proposition, researchers focused on the core benefits proposition, as a means defining the value and attributes of a given product with a description of physical features (Urban & Hauser, 1980). The intention was to visualize the meaningfulness and applicability to the specific user, who could then identify their own, internalized needs for it. The gap however was quickly identified – it was not the user, who is meant to define their value needs and ergo search for a solution. Instead, the developer should list these product strengths, further understood as particular values, and communicate them to a given user.

The first mentions of value proposition in the sense of a value delivery system can be seen in the 1985 McKinsey Quarterly, where a differentiation between product-oriented and value delivery-oriented systems can be seen (Bower & Garda, 1985). It is argued that businesses tend to restructure its approaches towards a market-oriented one, which assumes choosing, providing, and communicating the value (Lanning, 1998). Therefore, the value proposition process becomes an integral part of the business operation.

Lanning (Lanning & Michaels, 1988) then proceeded to restructure the original idea for the value proposition method, placing the importance on creating a resulting customer experience. In the VPC, this is established by the highlighting of the Products & Services as a value directly contributing to the customer's idea and possibility of the product implementation. The idea for forthright communication of the product features is established as a strength in and of itself. It is

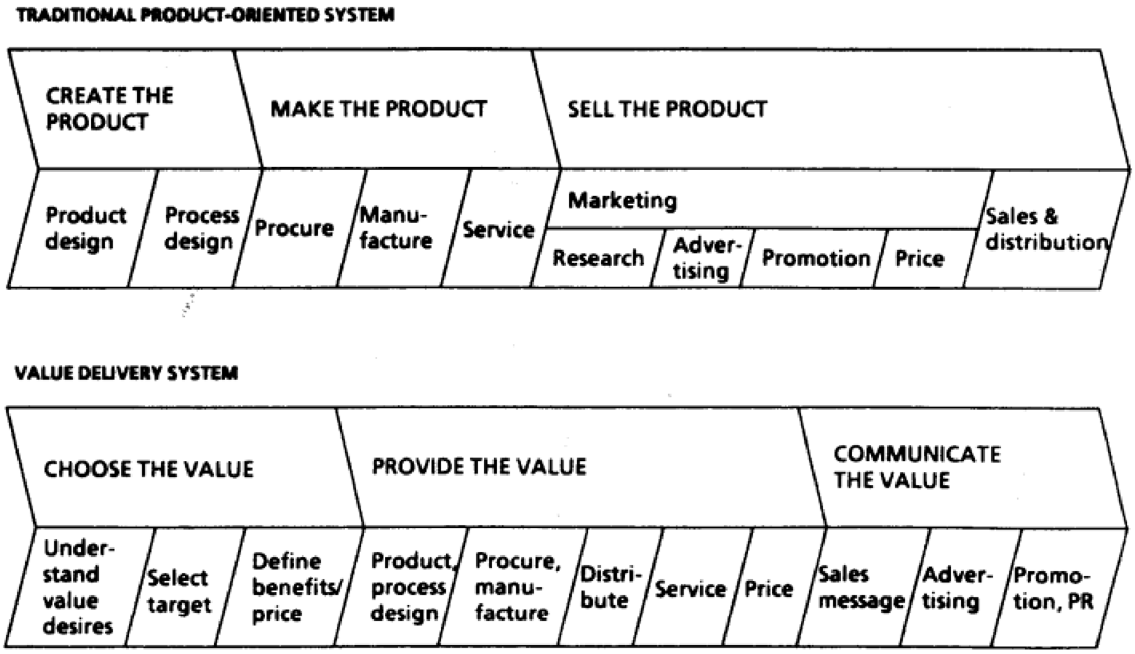

Figure 3.4: Differences between the product- and value-oriented systems, adopted from (Lanning & Michaels, 1988). Note the integration of the steps of previous methodology in the value delivery system.

argued that the customer needs to have a clear perspective on the usability and characteristics of the product beforehand in order to maximize their ability of envisioning its features in daily operations. Product / solution, despite its complexity, should not be a black-box, at least not in terms of values and features that it should provide (Lanning, 1998).

Before the values can however be effectively communicated, identification of the specific Value Proposition is needed. Rintamaki, Kuusela, and Mitronen (Rintamaki, 2007) defined a Value Dimensions Framework, which establishes the competitive advantage of a product / solution based on the multiple dimensions concerning the customer values, needs, requirements, etc. This framework highlights the importance of evaluation of non-countable, external factors that influence the customer's perspective. What differentiates VPC is its ability to connect (to some extent) these external factors with the product's Gain Providers directly. It does not however state the product's competitive advantage in terms of directly observable benefits, rather it focuses on the customer value fit. From the perspective of a Lean Startup, this allows for not quantifiable, but meaningful test of the product-market fit.

Another method, proposed by Karnbil et al. (Kambil, Ginsberg, & Bloch, 1996), focuses on comprehensive definitions of the company value proposition by establishing a connection between the product price and its performance. By doing so, the developer is able to outline the competitive advantage, while providing the list of benefits and trade-offs and their relationship with the competing solutions. This strategy involves maneuvering and redefining the VP based on the market needs, product penetration, and ability of implementation. A parallel can be drawn, as the Value Proposition Creation assumes frequent updates of the Canvas based on the added knowledge of the customer segment.

The Value Proposition Builder (Barnes, Blake, & Pinder, 2009) extends the idea of Lanning (Lanning & Michaels, 1988), (Lanning, 1998) by co-development of solutions, resulting from the customer feedback 3.5. From the perspective of development of complex AI products, this approach ensures that the realized framework not only satisfies the value need – it ensures an effective value capture and feasibility of implementation. From the perspective of the VPC, there is no effective method for communication and application of customer feedback. These processes are covered by the LEAN approach of Build-Measure-Learn (Ries, 2016), hence the iterative process of testing the solution across the customer segments is realized. Nonetheless, VPC places the importance of solution development mostly on the value provision – which is not incorrect, especially if potential customer segmenting is done effectively. From the perspective of AI / High Tech developments, some form of customer interaction at the stage of value definition is crucial. Due to its innate complexity and innovative factors, early stage integration of AI solutions into client's methods of value creation, delivery, and capture seems essential (Sjödin et al., 2021).

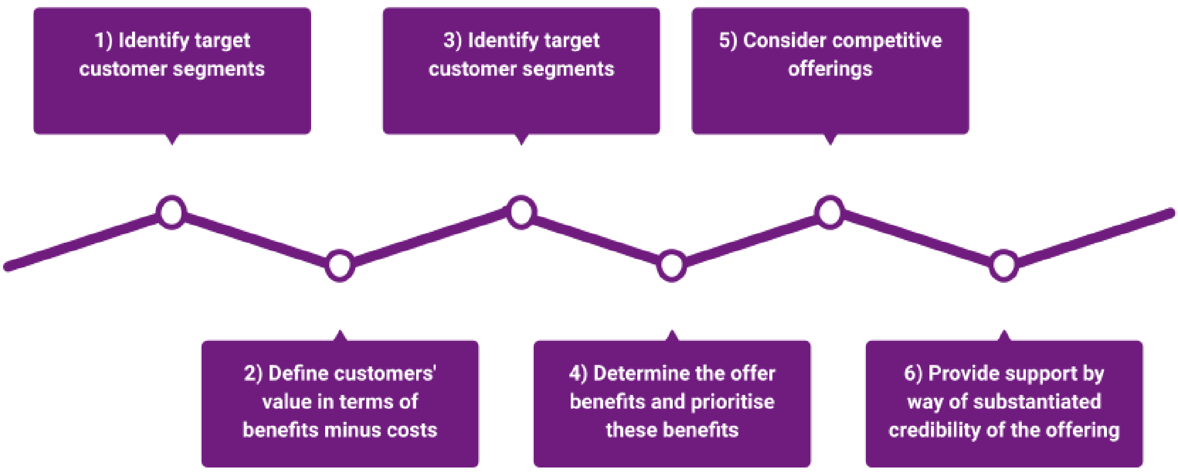

Figure 3.5: Value Proposition Builder framework, adapted from (Payne, Frow, Steinhoff, & Eggert, 2020), (Barnes, Blake, & Pinder, 2009). Note the consecutive steps integrating the value proposition and customer values, as well as the consideration of competing solutions.

Moreover, Value Proposition Builder provides the solution developers with a checklists that encompasses factors that the authors believe are necessary to be considered, as well as a method for their value hierarchical orientation. By promoting the idea of not creating products in the vacuum, Barnes et al. motivate the developers to consider external aspects that may influence value creation, communication, and capture (Barnes et al., 2009). In case of the Value Proposition Canvas, this is achieved by asking relevant, exploratory questions for every subsegment of the Value and Customer Maps. It should be noticed however that the open-ended, generalist questions may not always provide specific focus, when considering complex products / solutions. VPC main premise is the management and improvement of value proposition and business models (Osterwalder, 2014), yet the method is the same for the value management of products of varying complexity. This can be considered a strength – a simple tool is used for rapid evaluation and communication of the values, but additionally may be overly simplified, when dealing with compound issues.

The issue of multiple feasible entry markets is tackled by the Value Proposition Platform (Dennis, 2018), which assumes the development of specific value map for the main target map, alongside bordering, somewhat similar market segments. Such approach is especially useful, when dealing with the issue of technology conceptualization. By analyzing similar market entry points, it becomes possible for the developers to readjust, or completely change their approach, if an application becomes not feasible. The downside of this approach is the required time investment, which could otherwise be used for testing of the business hypotheses. VPC is strictly directional towards a single customer segment. However, due to its leniency, it becomes possible to readjust the value proposition and communication. Value Proposition Platform's additional strength is the emphasis on concise, immediate documentation that is transferable between the developer and potential customer. VPC relies on the graphical representation of the values and their internal relationships – useful for the business and tech developers, however not necessarily proper, when considering external communication.

3.4. Customer Discovery methodologies

Although the previously mentioned value description methods (Lanning & Michaels, 1988), (Kambil et al., 1996), (Rintamaki, 2007), (Barnes et al., 2009), (Dennis, 2018), as well as the evaluative VP framework (Payne et al., 2020) consider the customer segment research and customer interactions, a closer look should nonetheless be taken at the ways that developers research, understand, and judge the potential customer segments. Especially in the context of lean high tech startups, the initial assumptions about the market segments are often highly inaccurate due to lack of understanding of the actual customers, who could benefit from the value set proposed by the developer team. In the context of Value Proposition Canvas, a review of feasible methods for the Customer Map definition is necessary to gain sufficient understanding of the underlying processes.

Literature points to the lack of specific market need for the startup products or services as the main reason for their early stage failure (Le & Suh, 2019). This lack of market understanding, customer-need orientation, solution specificity originates in the startup developers not engaging sufficiently with the potential customer segments and hence not defining feasible paying client. The method for comprehension of the market requirements is often based on phrases such as “get out of the building” (Blank & Dorf, 2020), (Aulet, 2013), (Ries, 2016). In general – this is an effective approach, as it forces the developers to leave the comfort zone and engage in talks with potential customers, market actors, stakeholders, etc. However, one obvious deficiency of such advice is the lack of directionality. The early stage startups have troubles establishing, who the potential paying customer may in fact be. This is further complexified by the issue of high technology conceptualization – it becomes impossible to narrow down the search, if the use cases for the solution are not clearly defined.

Nonetheless, the “get out of the building” advice is the cornerstone of the tech startup market research. Literature highlights the importance of this recommendation, as startups that engage with potential customers in the early stages of development have higher chances of survival (Newbert, Tornikoski, & Augugliaro, 2020). Moreover, practices for the recognition of potential customers are described. Identification through Lean practices are often based in the creation and adoption of business models (such as the Business Model Canvas (Blank & Dorf, 2020)) in the form of Minimum Viable Business Models (MVBMs) (Ghezzi, 2020). Initial assumptions, conceived within the bounded rationality of the developers must be instantly checked within the real life application. It is argued that by setting up potential customer profiles, engagement within the market segment becomes possible. These iterative processes and application of feedback obtained from the “out of the building” engagement produces a clearer picture of the market segments, their needs, pains, and goals, while being organically implemented within the business and product development processes (Chengbin, Hongbin, Min, & Yongyan, 2022). Such practices can also be formed into an action framework (3.6), which more specific and completable steps for the customer value identification. The framework (da Luz Peralta, Echeveste, Martins, & Lermen, 2020), (da Luz Peralta, Echeveste, Lermen, Marcon, & Tortorella, 2020) involves the steps of Ideation – defining focus groups, and early assumptions, Value Prospection – business hypothesis testing and validation, and Requirements: identification, prioritization, and specification of customer pains and needs.

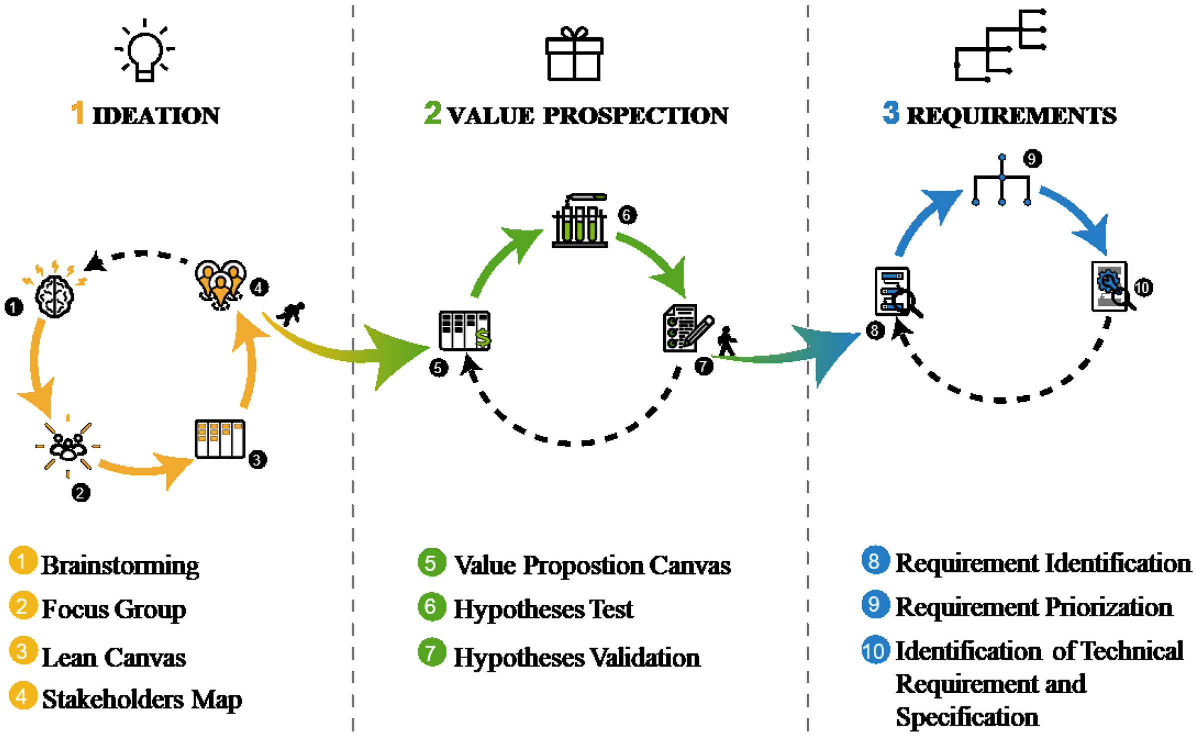

Figure 3.6: Framework for identification of Customer Value (da Luz Peralta, Echeveste, Lermen, Marcon, & Tortorella, 2020), (da Luz Peralta, Echeveste, Martins, & Lermen, 2020). Note the increasing specificity of the customer discovery process.

Determination and understanding of the customer segments should be followed by the customer involvement in the product development process. This should be understood as the consideration of their approach, implementation of feedback loops, analysis of customer values, etc. It seems that startups that involve their potential customers in the value and product development processes have better odds of successful market entry and continuing of operations (Newbert et al., 2020) Startup developers should pay attention to the ways of collaboration, data sharing, action timing, mutual agreements, and their fulfillment (Laage-Hellman, Landqvist, & Lind, 2018). The customer involvement should also be reflected in the adaptation, alignment, and review of the initially assumed business models (Piepponen, Ritala, Keränen, & Maijanen, 2022). Especially when considering AI / High Tech / Digital solutions, the level of complexity and novelty makes the involvement exceedingly important. In this way, the innovative nature of the product is considered by the both sides.

Another valuable insight into the customer discovery processes concerns further customer cooperation and interactions, beyond the initial involvement. Effective communication strategy should be planned and realized, as it forces the business developers to resolve issues of low trustworthiness of early startups (Konya-Baumbach, Schuhmacher, Kuester, & Kuharev, 2019). Moreover, it shifts focus to actual delivery of the value proposition by inspecting the compatibility of the Value Map with the Customer Value Map. This interaction through evaluation and adaptation of the value proposition ensures customer-centric attitude of the product developers, and the emphasis on solving actual problems and issues of the paying customer (Taylor, Hunter, Zadeh, Delpechitre, & Lim, 2020). Sustaining the competitive advantage may possibly be achieved by interacting with the customers, even non-payable ones. Their feedback, viewpoints, actor networks may add a significant amount of knowledge and understanding, resulting in more effective business development (Gasparin, Quinn, Green, Saren, & Conway, 2022).

3.5. Adoption of Artificial Intelligence solutions

By assessing at the Value Proposition methods, together with the analysis of the Value Proposition Creation, the literature study showed the strengths and weaknesses of the VPC method, its benefits, and challenges, especially when assessing complex technological solutions. The VPC is a LEAN, simple, yet effective way of assessing the gains and benefits of solutions in relationship to actual customer's needs and goals. However, the intrinsic complexity of AI solutions, together with the challenges imposed by the AI technologies conceptualization, confronts the straightforward methods proposed by the VPC. Additionally, in order to keep the VPC effective and understandable, changing the structure of the VP model goes against its initial assumptions.

It is argued that the value proposition of an artificial intelligence product is specific, and differs significantly from a regular value proposition creation process. In order to better understand the reasons for the user selection of the AI solutions over other conventional computational methods, a closer look is taken at the adoption of AI solutions. By doing so, the research goal becomes to learn and verify, if the reasons for the AI solution usage may have any impact on the AI product value proposition. The idea was to understand both successful and unsuccessful cases of AI solution adoption, look at the reasons behind them, and transpose them into the value domain. It must be remembered that the adoption factors themselves are not values itself. Rather, they are reasons, checkboxes that must be filled in order to successfully roll out an AI product. The challenge is to verify, whether these factors may have an impact on the value definition process.

On this basis, several key factors have been identified in the literature that influence the AI solution adoption. These attributes relate directly and should be reflected in the Value Proposition Creation methodology. In this way, the product development process can be considerate of the specific nuances that influence the value creation, communication, and capture.

1. **Data availability**

Certainly, one of the most significant strengths of the AI solutions is their ability of processing, comprehending, and operating in big data environments (Chang, 2020b), (El Bouchefry & de Souza, 2020), (Richbourg, 2018). The capacity of decision-making and procedure optimization, on-par or beyond human abilities is appealing to the end users (Muthukrishnan et al., 2020), (Borges et al., 2021), (Andriotis & Papakonstantinou, 2018). This level of efficiency is only achievable with a high degree of data availability, and subsequent quality, storing, organization, and transferability (Moorman et al., 2020), (Piepponen et al., 2022), (Saw & Ng, 2022), (Volkmar, Fischer, & Reinecke, 2022). Moreover, the integration of previously used models and methodologies can be vital to AI development and tailoring of the proposed solution (Balakrishnan et al., 2020, November), (Volkmar et al., 2022).

2. **Integration with current methods of operation**

The innovative aspect of the artificial intelligence approach relies on the solution's adaptability and imitation of human behaviors (Muthukrishnan et al., 2020), (Borges et al., 2021), (Andriotis & Papakonstantinou, 2018), (Valle-Cruz et al., 2021). Therefore, the operation methods of the domain, within which the AI is to be implemented must be studied and accounted for. Although the behavioral aspects of an AI solutions try to emulate human actions, their realization, and specific way of operation may significantly interfere with the previous approaches (Volkmar et al., 2022), (Valle-Cruz et al., 2021), (Kaplan & Haenlein, 2020). As an example, the DRL algorithms may quantify, and predict the necessary actions, they are also able to optimize the decision pathways that should be undertaken (Andriotis & Papakonstantinou, 2018). Such approach may differ from the previously assumed methods for decision making, hence altering the methods of business operation (Harvey & Gowda, 2021).

3. **Experiences of the stakeholders**

Similarly to the aspect of integration of the AI solutions with the current methods of business operation, a certain degree of uniformity, agreeableness, and understanding of the involved stakeholders is necessary. By determining their methods of operation and relationship with the end user, as well as their anticipations and fears resulting from the implementation, the developed product may be well aligned with the needs (Desouza, Dawson, & Chenok, 2020), (Zuiderwijk et al., 2021), (Sun & Medaglia, 2019). This is explicitly required for the Artificial Intelligence products, as their functionality often directly supports, or overwrites human actions (Muthukrishnan et al., 2020), (Borges et al., 2021), (Andriotis & Papakonstantinou, 2018), (Valle-Cruz et al., 2021). Strong communication of the value proposition of AI products with 3rd party actors is needed to address and mitigate resulting issues (Fatima, Desouza, & Dawson, 2020), (Meske, Bunde, Schneider, & Gersch, 2022), (Harvey & Gowda, 2021).

4. **Internal capacity for implementation**

The implementation of AI solutions is not necessarily straightforward. Besides the need for the availability and transferability of data, synthesis with current practices, and alignment with stakeholders, the integration within the internal business structure may be ambiguous (Kaplan & Haenlein, 2020), (Saw & Ng, 2022), (Borges et al., 2021), (Reim, Åström, & Eriksson, 2020), (Valle-Cruz et al., 2021). Because the AI solutions often aid, or replace human activities, the evaluation of their added value is challenging. Moreover, the perceived benefits of AI use may not be clear due to individual attitudes towards the technology (Lichtenthaler, 2019), (Gebauer et al., 2020, 3). Therefore, understanding the customer's capacity for implementation of Artificial Intelligence is vital, as imposed changes may be disruptive to the standard business methods of operation (Volkmar et al., 2022).

5. **Previous ICT experience** The increasing capacities and widespread use of the Information and Communication Technologies (ICT) were the preceding factors responsible for the rising interest in Artificial Intelligence solutions (Meske et al., 2022). By enabling information- and data-based solutions, companies became acquainted with innovative approaches and established a strong base for further implementation of AI products (Verhoef et al., 2021), (Wirtz, Weyerer, & Geyer, 2019). What is more, AI draws directly from the resources and methodologies of ICT (Chang, 2020a). Therefore, a strong connection and previous experiences with ICT solutions may be considered as an indicator of AI feasibility (Li et al., 2017).

6. **Perceived costs of implementation**

Potential clients and users of AI products may not be aware of the costs of AI solution implementation. Aside from the required computational capacities, potential data transfers and security should be considered (Desouza et al., 2020), (Golding & Nicola, 2019). Moreover, AI influence on the business operations may alter the cost schemes. Additionally, the perceived cost may differ based on the customer's qualitative evaluation of the AI applicability and their attitude towards the innovation (Borges et al., 2021), (Lichtenthaler, 2019).It may also be the case that customers with highly developed ICT solutions may have lower costs of AI introduction due to the already existing systems (Verhoef et al., 2021), (Wirtz et al., 2019).

7. **Perceived benefits of implementation**

Similarly to perceived costs, client's awareness of potential benefits, both financial and operational plays an important role in the AI value proposition process (Desouza et al., 2020), (Golding & Nicola, 2019). As the Artificial Intelligence emulates human intelligence, the potential advantages go beyond the increasing of operational efficiency (Borges et al., 2021), (Chang, 2020b), (Lichtenthaler, 2019), (Wirtz et al., 2019). It should be realized by both – the developer and the client – that the AI application may affect domains previously not considered by other solutions. The necessity of quantifying these implications in terms of possible benefits stands at the forefront of AI VP process (Meske et al., 2022).

8. **Differentiation from other solutions**

Although Artificial Intelligence solutions offer significant performance increase, especially in the big data environments(Borges et al., 2021), (Chang, 2020b), (Balakrishnan et al., 2020, November) their usability, robustness, and efficiency may be advantageous in other areas (Borges et al., 2021), (Volkmar et al., 2022), (Richbourg, 2018). It becomes necessary to understand the domain of application, as well as the potential uses and their benefits (Valle-Cruz et al., 2021), (Zuiderwijk et al., 2021). By comparing and differentiating AI products from other available solutions, it becomes possible to showcase their capacities and tailor the usability to the customer's needs.

9. **Organizational agility**

Being often set as a hallmark of the digital transformation, implementation of Artificial Intelligence products requires a certain degree of organizational agility, ability to absorb and capture the value of innovative solutions (Andrew, 2017), (Haefner, Wincent, Parida, & Gassmann, 2021). Therefore, AI introduction in rigid organizational environments may be unsuccessful due to its impact of their internal processes, methods of operation, performance tracking, etc.

(Reim et al., 2020), (Borges et al., 2021), (Kaplan & Haenlein, 2020), (Saw & Ng, 2022). AI value proposition should take into consideration these impacts as well as the consider the methods for mitigation of their negative implications on an organizational level (Allam, 2016).

10. **Organizational structure**

Research indicates that AI may not provide definite answers, but rather provide preliminary solutions (e.g., probability-based forecasts) (Sjödin et al., 2021),(Tarafdar et al., 2019, 4). Therefore, human interpretation of these outputs is still needed. It becomes necessary to understand the organizational structure and capacity for digital transformation and AI implementation (Allam, 2016), (Haefner et al., 2021). The impact on internal organizational structure must also be considered, as AI allows for new methods of operation (Kaplan & Haenlein, 2020). Artificial Intelligence value proposition also affects the way organizations function; safety, new internal responsibilities, and organizational management must be considered (Andrew, 2017), (Agrawal, Gans, & Goldfarb, 2018).

11. **Technology and innovation awareness**

AI implementation may lead to the reestablishment of the company's entire innovation process (Allam, 2016). AI's capacity for reasoning on-par and beyond human abilities, as well as ability to handle vast amounts of data reshapes the possibilities and ways that users think about innovation (Moorman et al., 2020). Implementation of AI opens the doors to future innovation and application of new, inventive solutions (Agrawal et al., 2018), (Haefner et al., 2021), (Borges et al., 2021), (Kaplan & Haenlein, 2020). Specifically, overcoming of the human capabilities constraints may allow for diffusion and implementation of technologies that were previously unattainable (Bughin et al., 2017). AI should be therefore also considered as a innovation generator, which affects every aspect of organization operations (Haefner et al., 2021).

12. **Leadership support**

In order to harness the potential of Artificial Intelligence solutions, management must rethink and reinvent the ways the organizations are operating (Haefner et al., 2021). AI value proposition should be aligned with the organizational methods for value capture (Kaplan & Haenlein, 2020). The definition and adjustment of there methods must be met with corresponding adaptation of the AI products by the developers. Moreover, the fact that AI solutions imitate human behaviors results in understandable caution, and questioning of these practices.

Strong leadership must be seen within the organization, in order to understand, communicate, and mitigate potential problems of implementation (Smith & Green, 2018), (Benbya, Davenport, & Pachidi, 2020), (Reim et al., 2020), (Volkmar et al., 2022).

13. **Trust in AI solutions**

Relating to the notion of leader support within the customer organization, the factor of trust in AI application, their efficiency, safety, and reliability is crucial from the perspective of a value proposition. Especially for Artificial Intelligence, the concerns among users regarding their efficacy, cognitive abilities, as well as the true nature of their inner functions are high (Lichtenthaler, 2019), (Davis, 1989). Literature points towards building trust in innovative solutions through understanding, ease of use, predictability, and perceived usefulness (Rossi, 2018), (Glikson & Woolley, 2020), (Borges et al., 2021), (Davis, 1989). From the perspective of the product development, it is crucial that these aspects are accounted for in the design and communication processes. By mitigating the risks and uncertainties correlated with the trustworthiness of AI solutions, the specific value proposition becomes coherent and subsequent value capture is enabled (Siau & Wang, 2018), (Reim et al., 2020), (Smith & Green, 2018).

14. **Bias in AI**

What stems from the trust in the efficacy of AI solutions is the necessity to acknowledge and comprehend certain biases visible in the artificial intelligence applications. Considering the fact that AI can obtain, comprehend, and apply knowledge in the form of distilled contextual data (Chang, 2020b),(Lichtenthaler, 2019), it must be recognized that intelligence significantly differs from wisdom, which assumes the ability to conceptualize the surrounding environment and attribute moral judgement (Clayton, 1983). This predicament may lead to situations, where the taken decisions are only optimal from the perspective of the data domain. Therefore, bias is AI can be recognized as the bias of the application itself – where certain decisions are taken without the consideration of external factors (Nelson, 2019), (Panch, Mattie, & Atun, 2019), (K. Johnson, Pasquale, & Chapman, 2019), as well as the bias towards AI – where the user is concerned with the technology's ability to distinguish the acceptable decisions (ergo, referring to the notion of trust in the AI solution) (Rossi, 2018). From the perspective of the AI solution adoption and value proposition, it becomes necessary to understand these biases and address the possible repercussion (Siau & Wang, 2018), (Reim et al., 2020), (Smith & Green, 2018).

15. **Moral, ethical, and social concerns**

The final factor that in the eyes of this research affects the adoption of the AI products are the moral, ethical, and social concerns, surrounding the application, use, and consequences of their implementation. Without a doubt, the imitation or replacement of the human logic actions raises significant concerns to the principles of our interactions with technology (Miernicki et al., 2021), responsibility (Etzioni & Etzioni, 2017), (Russell, Hauert, Altman, & Veloso, 2015) outcomes of the decision making (Bostrom, 2003), collateral effects (Ouchchy, Coin, & Dubljević, 2020), among others. The issues concerning the superintelligent AI, mainly singularity (Bostrom, 2003) and overpowered, unguided development, present questions of moral eligibility (Belk, 2021), (Russell et al., 2015) of these technologies. Also, the issues of social exclusion, lessening the adaptability of an individual must be considered (Perc, Ozer, & Hojnik, 2019). What the current developers of AI have to realize is that these concerns must be recognized and studied already, as their future impact may not be controllable, nor sufficiently determinable if left to chance. From the perspective of the AI adoption, lack of solid understanding and evaluation of possible ethical and social concerns may be a significant obstacle and blocking factor. Moreover the values proposed by the AI technologies cannot be sufficiently impactful, if ethical values are not considered in the first place (Boddington, 2017).

3.6. Literature review - discussion

This chapter encompasses the literature findings on the developments of Artificial Intelligence, methodology of the Value Proposition Creation model together with its defining segments, as well as the factors that influence the adoption of the AI solutions. By studying the relevant literature, it becomes possible to understand the notions governing the development of technological domains, together with the methods used to describe and analyse them. It became apparent that the concepts guiding the advancement of AI technologies can be reflected in our attempts at defining and communicating their specific values. Moreover, the key aspects of the value proposition methods can be reflected in the factors that guide the technology adoption and its subsequent use.

Artificial Intelligence technology can be considered as one of the most prominent and important technological domains in the present day. AI solutions have the potential of reorienting and improving our operations across the entire spectrum of professional domains. Combining their agility in big data environments and potentially superhuman computational efficacy, AI solutions present themselves as remarkably valuable tools, with potential applications essentially in every market. However, because of their innovative nature that drastically reshapes the methods in which organizations are run, as well as vastly unknown implications towards how we operate, their adoption processes are complex and require appropriate definition and attention.

From the perspective of a AI spinoff, the value proposition of an AI product may be specifically difficult for these reasons. The commonly found methods, such as the VPC, are highly valued among startup entrepreneurs. Nonetheless, it is unknown, if these methodologies are adequate for the adoption of AI products by potential customers. Therefore, based on the literature findings, it becomes viable to further determine how the value proposition methodology can reflect the upon the factors are responsible for AI adoption among users.

3.6.1. Factors influencing the adoption of AI solutions

In order to define a conceptual model, the relevant adoption factors must be listed. Based on this list of aspects, the empirical analysis may be conducted. Table 3.1 presents the list of factors influencing the adoption of an Artificial Intelligence solution with the relevant literature references.

Table 3.1: Factors influencing the Value Proposition of an Artificial Intelligence solution, with relevant literature references.

Factor	Literature reference
Data availability	Chang, 2020b; El Bouchefry and de Souza, 2020; Richbourg, 2018; Muthukrishnan et al., 2020; Borges et al., 2021; Andriotis and Papakonstantinou, 2018; Moorman et al., 2020; Piepponen et al., 2022; Saw and Ng, 2022; Volkmar et al., 2022; Balakrishnan et al., 2020, November
Integration with current methods of operation	Muthukrishnan et al., 2020; Borges et al., 2021; Andriotis and Papakonstantinou, 2018; Valle-Cruz et al., 2021; citevolkmar2022artificial; Harvey and Gowda, 2021; Kaplan and Haenlein, 2020

Continuation of Table 3.1	
Factor	**Literature reference**
Experiences of the stakeholders	Desouza et al., 2020; Zuiderwijk et al., 2021; Sun and Medaglia, 2019; Fatima et al., 2020; Harvey and Gowda, 2021; Meske et al., 2022; Muthukrishnan et al., 2020; Borges et al., 2021; Andriotis and Papakonstantinou, 2018; Valle-Cruz et al., 2021
Internal capacity for implementation	Kaplan and Haenlein, 2020; Saw and Ng, 2022; Borges et al., 2021; Reim et al., 2020; Valle-Cruz et al., 2021; Lichtenthaler, 2019; Gebauer et al., 2020, 3; Volkmar et al., 2022
Previous ICT experience	Meske et al., 2022; Li et al., 2017; Verhoef et al., 2021; Wirtz et al., 2019; Chang, 2020a
Perceived costs of implementation	Desouza et al., 2020; Golding and Nicola, 2019; Borges et al., 2021; Lichtenthaler, 2019; Verhoef et al., 2021; Wirtz et al., 2019
Perceived benefits of implementation	Desouza et al., 2020; Golding and Nicola, 2019; Borges et al., 2021; Lichtenthaler, 2019; Chang, 2020b; Wirtz et al., 2019; Meske et al., 2022
Differentiation from other solutions	Borges et al., 2021; Chang, 2020b; Balakrishnan et al., 2020, November; Volkmar et al., 2022; Valle-Cruz et al., 2021; Zuiderwijk et al., 2021; Richbourg, 2018
Organizational agility	Andrew, 2017; Haefner et al., 2021; Reim et al., 2020; Borges et al., 2021; Kaplan and Haenlein, 2020; Saw and Ng, 2022; Allam, 2016
Organizational structure	Sjödin et al., 2021; Tarafdar et al., 2019, 4; Allam, 2016; Haefner et al., 2021; Andrew, 2017; Agrawal et al., 2018; Kaplan and Haenlein, 2020
Technology and innovation awareness	Allam, 2016; Moorman et al., 2020; Agrawal et al., 2018; Haefner et al., 2021; Borges et al., 2021; Kaplan and Haenlein, 2020; Bughin et al., 2017

Continuation of Table 3.1	
Factor	**Literature reference**
Leadership support	Haefner et al., 2021; Kaplan and Haenlein, 2020; Smith and Green, 2018; Benbya et al., 2020; Reim et al., 2020; Volkmar et al., 2022
Trust in AI solutions	Lichtenthaler, 2019; Rossi, 2018; Glikson and Woolley, 2020; Borges et al., 2021; Siau and Wang, 2018; Reim et al., 2020; Smith and Green, 2018; Davis, 1989
Bias in AI	Chang, 2020b; Lichtenthaler, 2019; Nelson, 2019; Clayton, 1983; Panch et al., 2019; K. Johnson et al., 2019; Rossi, 2018; Siau and Wang, 2018; Reim et al., 2020; Smith and Green, 2018
Moral, ethical, and social concerns	Miernicki et al., 2021; Etzioni and Etzioni, 2017; Russell et al., 2015;Bostrom, 2003; Ouchchy et al., 2020; Belk, 2021; Perc et al., 2019; Boddington, 2017

3.6.2. Evaluation of Value Proposition practices

Payne (Payne et al., 2020) suggest that the following five phases constitute a comprehensive value proposition development. By analyzing individual steps of the process, the authors evaluate and present the most significant aspects that are relevant to the systematic way of providing value in the business to business (B2B) setting (Anderson, Narus, & Van Rossum, 2006), (Anderson, Kumar, & Narus, 2007). However, it points to several universal truths that are applicable to each value proposition methodology. Figure 3.7 presents the framework for comprehensive value proposition development, showcasing the dependencies of the phases and the central point of the Value-in-Use, defined by interactions within the customer segments, their relevant stakeholders and actors.

1. **Phase 1: Value design and assessment**

The first phase focuses on the evaluation of internal capacities, resources, and abilities. Moreover, customer and competitor research begins. These actions are done in accordance to the established business model (in case of early stage startups, the business models are often determined during the value proposition). Value proposition is defined using the key

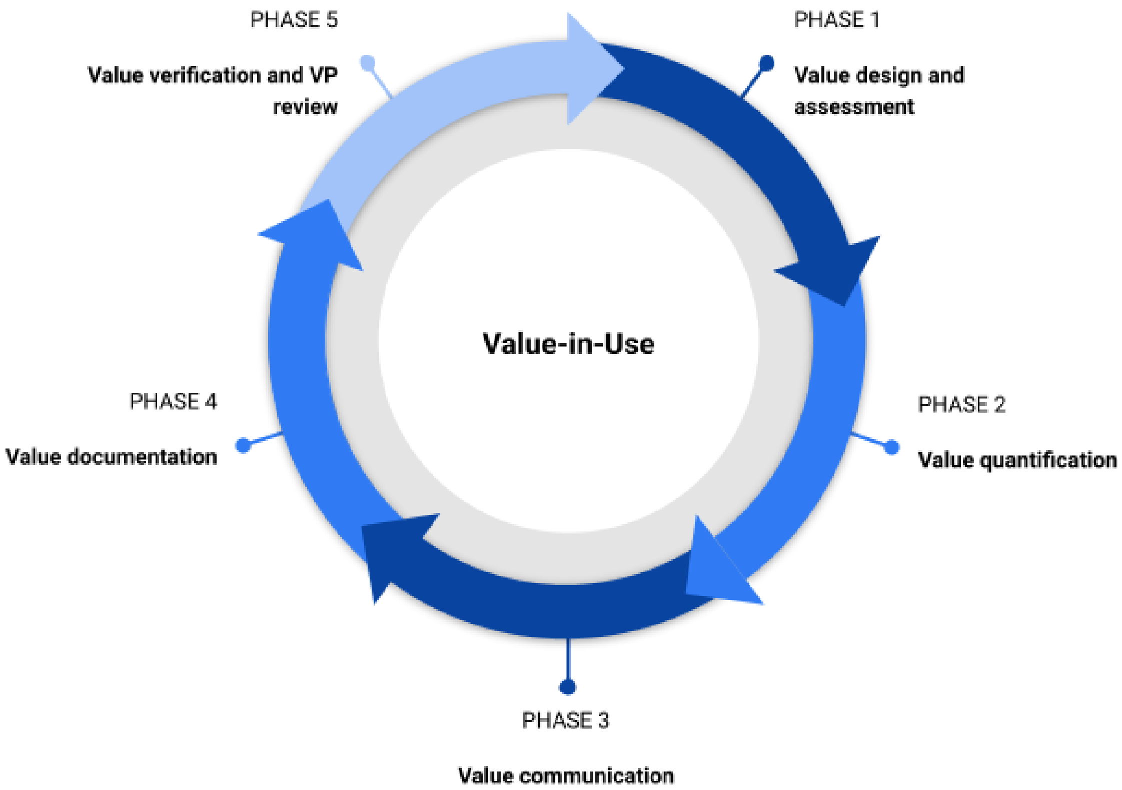

Figure 3.7: Framework for comprehensive value proposition development (Payne, Frow, Steinhoff, & Eggert, 2020). Note the circular nature of the process and the central dependency on the Value-in-Use, defined and characterized by the interactions with the customer and stakeholders.

benefits, strengths, differentiating advantages, in conjunction with the determined customer segment. Emphasis should be placed not only on the functional and economic values, but also social, environmental, emotional, legal, etc. What is more, VP testing is carried out with potential customer, to establish the model fitness.

2. **Phase 2: Value quantification**

Next step involves specific VP quantification and comparison with real life application. This ensures that the solution is not created in a vacuum of its own reality. Quantification is also carried out for competing solutions and values represented by the customer. Both qualitative and quantitative data should be obtained for sake of the framework accuracy. What is more, certain specificity has to be applied to the value proposition in order to connect it directly with a defined customer. Several customer segments may place different weights on different values, and their value structures can be significantly dissimilar.

3. **Phase 3: Value communication**

Following phase combines the methods for effective value communication with the customer and several marketing mechanisms. It is highlighted that the value proposition is also to be communicated with stakeholders and actors that are (in)directly involved in the process of the product implementation and assimilation. It is also at this stage that internal team alignment must happen, so that every department responsible for the product realization is aware of the values that it must represent.

4. **Phase 4: Value documentation**

In phase four, focus is brought to the methods of internal documentation, progress tracking, ways of evaluation and measurement. It is argued that the Value Proposition should also be a mechanism for the assessment of the internal development course, profitability, and functionality. The VP becomes the point of orientation, a corner stone for the product development. It should be used not only externally, but also (or maybe even primarily) internally to ensure plan and vision adherence, as well as feasibility.

5. **Phase 5: Value verification and Value Proposition review**

Final phase in this framework deals with verification, authentication, and review of the value proposition assumptions. The developers should look back at the previous stages of the process and analyze the completion of sub-tasks, as well as their efficiency. Feedback mechanisms should be in place that allow for information flow from the customer and stakeholders back into the development team. Validation of the proposed values, as well as methods for their realization in the proposed solution is an iterative process, hence it is argued that the entire framework is circular in nature. The previous steps should be revisited and accounted for throughout the development, sale, implementation, and support stages, to serve as guidance and means of verification.

3.6.3. Evaluation of Customer Discovery practices

By looking at customer discovery methods described in the literature, the following list of steps can be extracted as an effective approach to this process (3.8). It highlights the important aspects and key objectives that should be realized by the startup developers, especially in the early stages of business development.

1. **Identify**

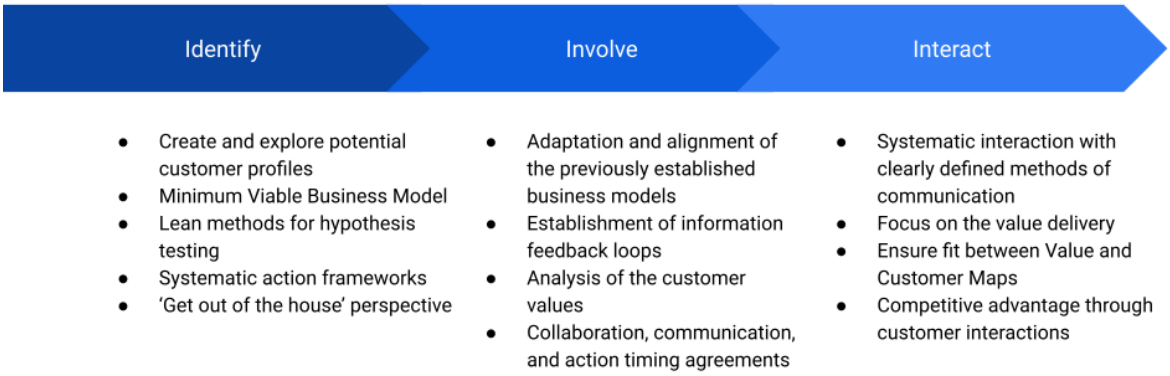

Figure 3.8: Three stages of the customer discovery process

The early phases of customer identification begin with the creation and exploration of potential customer profiles. Determination of Minimum Viable Business Models (similar to MVPs) is advised as a Lean method for market segment identification. Action frameworks may me implemented or developed for systematic analysis of these suppositions. The assumptions should be written in forms of testable hypothesis, which can be iteratively examined and updated. It is crucial that the startup developers do not carry out these actions 'in house', rather that they engage with stakeholders and actors, and explore their potential networks.

2. **Involve**

By involving the customers in the product development process, successful market entry and product-market fit can be assured. The customers' and other relevant stakeholders' expertise should be used for the adaptations and alignment of the previously established business models. Moreover, startup developers should look into the implementation of information feedback loops, and the analysis of customer values. By considering these aspects, the efficacy of the value proposition increases, and value capture is enabled. Moreover, at this stage, methods of collaboration, communication, action timing should be aligned and agreed upon with the customers.

3. **Interact**

The customer involvement process should eventually transform into a systematic interaction, with clearly defined methods of communication and collaboration on certain product issues. At this stage, the startup developers focus on the value delivery, therefore ensuring the fit between the Value and Customer Maps. It is argued that competitive advantage can be furthered through customer interaction, and actor network exploration. The acquisition of their information and knowledge may aid in effective business development, product introduction, and future projects.

By looking at the Value Proposition as a process and referring the Value Proposition Creation to the commonly found VP stages, a more thorough understanding of the methodology is achieved. As the VP process for high-tech solutions is complex and requires a higher level of accuracy and forethought, generating a set of useful practices and attributing them to VPC for an AI technology might allow the solution developer to be more aware of the situation, effectively quantify the progress, and plan ahead. As one of the assumption of this research is to keep the Canvas methodology as agile and simple as possible, an in-depth look at the surrounding processes, their importance, and meaning is necessary. Therefore, by pinpointing the VPC's lacking areas, as well as the strong points, a strategy for the needed VP process adjustments can be presented.

4 Conceptualization

This chapter describes the process of conceptualization, which considers deriving meaning from the previously found scholarly knowledge and forming the approached necessary for the case study. First, a conceptual model for the adoption of AI solutions based on the literature findings is presented. The model serves as a backbone for the empirical analysis, which through semi-structured interviews confirms and elaborates on the model. Afterwards, the Value Proposition Creation framework is evaluated upon, through the lenses of Value Proposition and Customer Discovery methodologies. In this way, an outlook on the VPC method can be obtained; its general strengths and weaknesses are discussed in relation to the established methodologies. Here it should be highlighted that the specific choice of VPC as a main VP method for technology university spinoffs is made on the basis of its comprehensiveness, availability, and uniformity.

4.1. Conceptual model of Artificial Intelligence solution adoption

The factors defined in 3.1 are used as a basis for the conceptual model in this research. Having derived the aspects from the literature, a clear, yet broad view is obtained on the adoption of AI solutions. In order to structure the model and obtain a more comprehensive perception of the factor interplay and possible dependencies, several groups are defined that collectively describe the factors. The following groupings of factors are made: Product & Implementation, Expertise, Market, Organization, and Miscellaneous. Such organization of factors allows a clear arrangement of the mutually related factors, in addition to defining encompassing domains for further evaluation during the expert interviews.

Product & implementation factors correspond to these product aspects that are required from the organization for the feasibility of the AI operation. Expertise factors define aspects of internal and external experiences of the organization, which may affect their ability of capturing the value and diffusing the innovation. Market factors define the perceived cost/benefit analysis of the solution, together with the consideration of alternative (non-AI) approaches. Organizational factors define supervisory, managerial, and knowledge-based aspects of the organization that may influence the internal competencies, specifically from the regulatory perspective. Finally, Miscellaneous factors consider the confidence, expectations, and considerations of an organization that might potentially shape and configure their methodology and approach towards Artificial Intelligence solutions.

Figure 4.1 presents the conceptual model of adoption of an Artificial Intelligence solution, based on the factors found in literature.

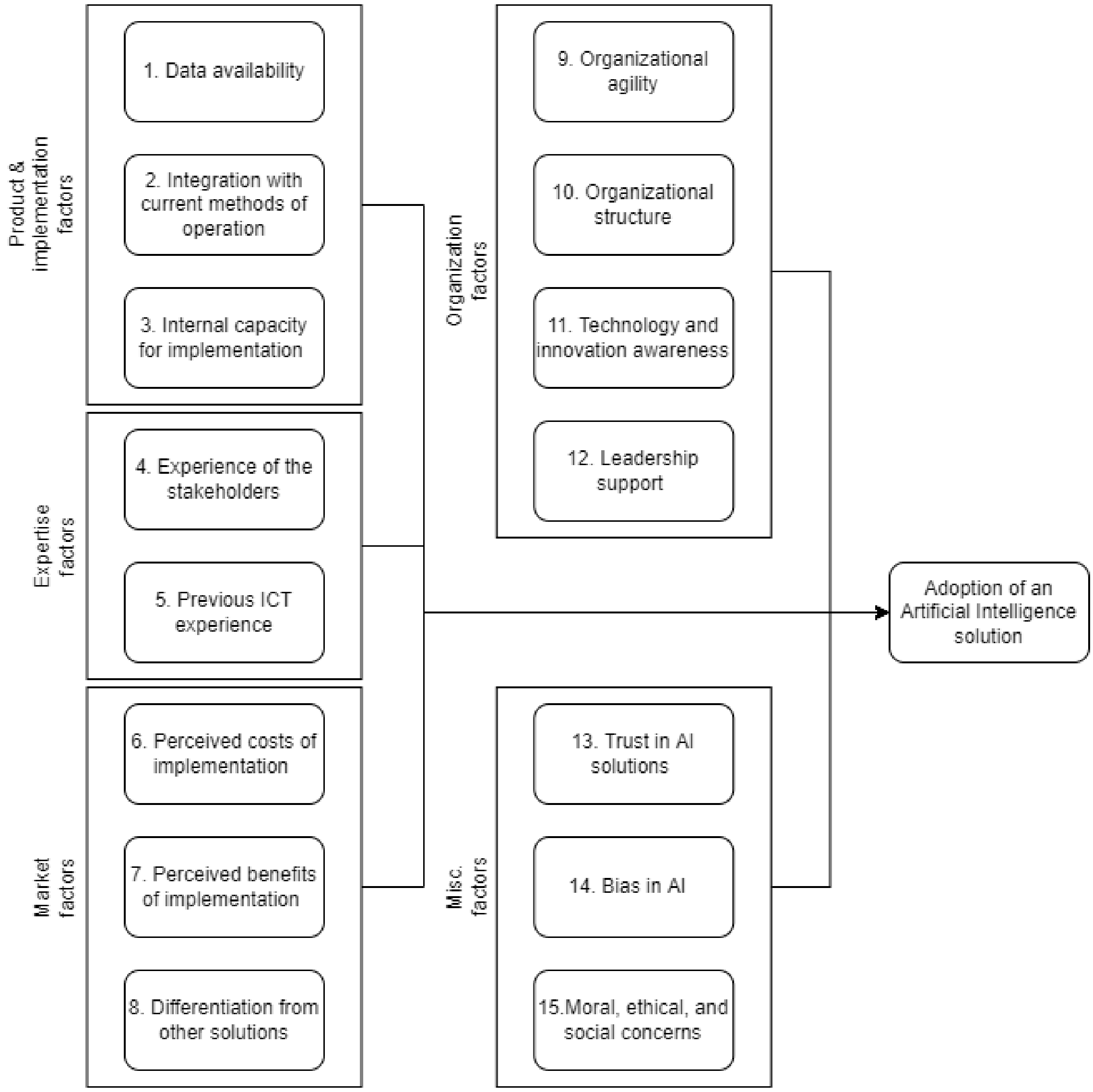

Figure 4.1: Conceptual model for the adoption of an AI solution

Looking at the conceptual model for the AI solution adoption, it becomes clear that a direct relation to the Value Proposition models cannot be made. The aspects that the adoption model encloses are technical, deterministic, whereas the VP models operate in the domains of values and benefits derived from said technical aspects. Adoption of the solution itself already assumes that the customer has agreed (or is in the negotiation process) to the proposed value proposition. Therefore, ensuring the adoption factors of the AI, or any high-tech solutions becomes the crucial aspect during the proof-of-concept, or feasibility study stage. The adoption factors are hence treated as benchmark, checkboxes that have to be ensured.

On the other hand, Value Proposition, and specifically the Value Proposition Creation model deal with highly conceptual, value-based variables that correspond to the market, user, customer needs, goals, and pains. That is why the gains and benefits that are listed in the VPC model are precursors to a solution definition, which then can be successfully marketed and adopted by the customer. The value proposition domain, as shown in 3.4, comes before the value provision (in a form of a solution) to the customer. Hence, value proposition shapes the value creation, provides a background on which solution adoption factors must be realized and ensured.

It is therefore reasonable to understand, how the aspects that were responsible for the Artificial Intelligence solution adoption could affect the value proposition. By working backwards, with both successful and failed implementations, the research hopes to showcase how the adoption factors could affect the value proposition of an AI solution. By using the VPC as a standard Value Proposition method for the university spinoffs, by understanding its methodology, and defining its strengths and weaknesses, the research tries to unveil how the commonly found AI adoption factors can be acknowledged already at the VP stage. Therefore, by adequately defining the value background for the solution development, the adoption factors can be more effectively fulfilled. By doing so, the chances of successful AI product commercialization and implementation increase.

Having obtained the common Artificial Intelligence adoption factors, a closer look can be taken at the practices of the Value Proposition Canvas. By reflecting upon the methodology, VPC's benefits and inadequacies, an approach for the inclusion of the adoption framework within the VPC process can be more effectively defined.

Table 4.1: Evaluation of the Value Proposition elements of the Value Proposition Canvas, inspired by the *Toward a comprehensive framework of value proposition development: From strategy to implementation* (Payne, Frow, Steinhoff, & Eggert, 2020)

Value Proposition element	Reasoning
Integration with the business model	VPC is directly related to the elements of the Business Model Canvas.
Differentiated value benefits	VPC separates the proposed values into Pain Relievers, Gain Creators, and specific Products & Services.
Emphasis on price	The process asks directly for financial improvements / cost reduction in the Customer Segment
Experimental focus	The method is complaint with the LEAN approach of Build-Measure-Learn.
Value-in-use	Values are integrated into the distinct Products & Services that must correlate with user requirements.
Integrated VP design	The process is based on open-ended, exploratory questions that are asked to the business developer in order to guide the VP definition.
Value communication	Value map is directly related to the specific aspects of the Customer Segment.
Value quantification	VPC does not directly quantify the values; qualitative approach is used
Value documentation	There is no way for documenting the obtained values for the specific client, other than the Canvas representation.
Value verification	There is no method for verifying the correlation, accuracy, or weight of the value in relationship to the customer.

4.2. Value Proposition Creation - practices assessment

In the research paper on frameworks of value proposition development, Payne et al. provide a comprehensive overview of elements that constitute effective value proposition process (Payne et al., 2020). Table 4.1 provides the list of these elements and the emphasis placed upon them within the VPC.

By considering this evaluation of the Value Proposition Creation method, certain strengths and shortcomings can be distinguished. To begin with, a major benefit of the Canvas is its direct integration with the business model, specifically the Business Model Canvas (figure 4.2). VPC's ability to zoom in on the primary aspects of the BMC, as well as to relate them with the other elements is a definite advantage, especially when considering the validation of business hypotheses using the Lean methodology of rapid Build-Measure-Learn. Similarly, Canvas's differentiation of specific attributes of the values – perceived pains and gains – demands a certain level of separation of the product aspects that encapsulate distinct qualities. As such, a higher level of integration can be achieved, and moreover, aspects other than financial gains are encouraged. Nonetheless, a strong emphasis on the financial improvement is seen, specifically in the guiding questions stated by Osterwalder (Osterwalder, 2014). This priority given to the monetary values, reflected in the financial improvements / cost reductions, is the driving force behind establishing competitive advantage, as well as focus on the financial stability in the early stages of MVP development.

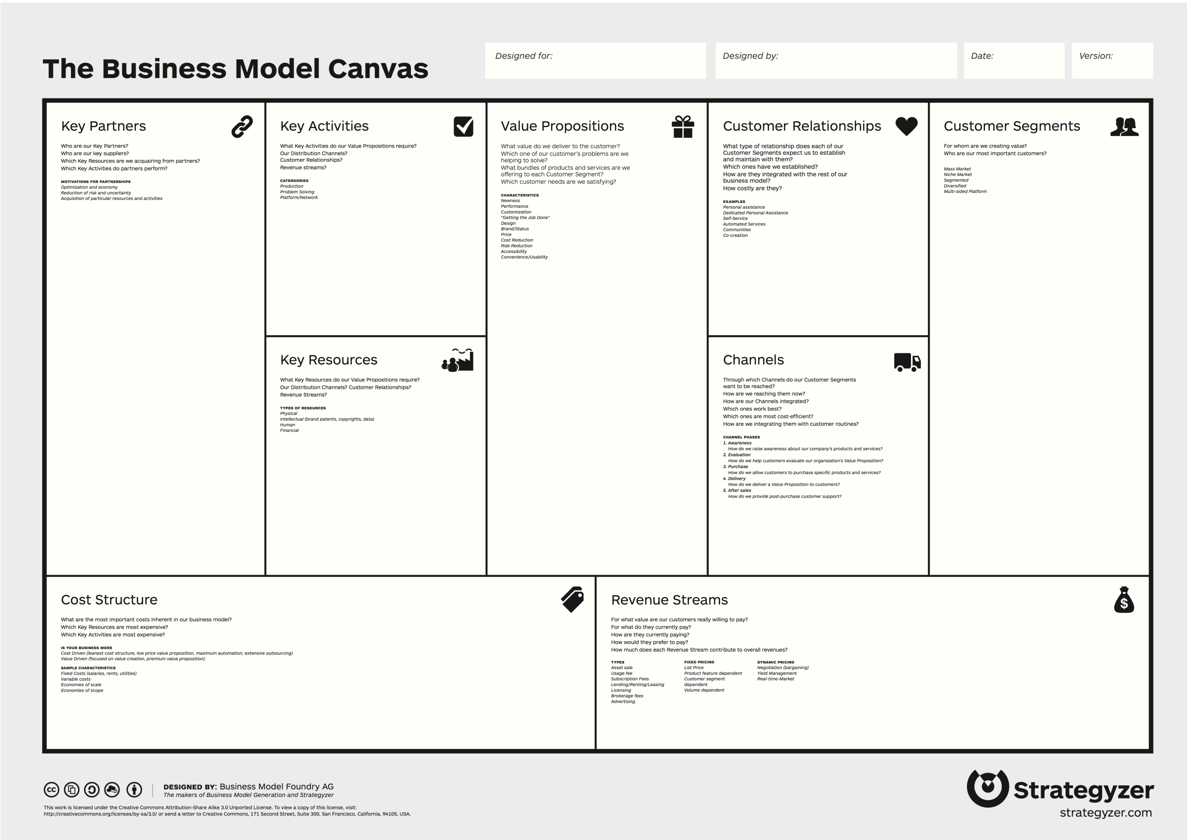

Figure 4.2: Business Model Canvas; VPC methor relates directly to the Value Proposition and Customer Segment fields (Osterwalder, 2014)

A key strength of the VPC and the reason, why is it favored in the early stage startup development is its compatibility with the Lean approach proposed by E. Ries (Ries, 2016). The idea behind the canvas, as well as its main methodology is the compliance with a rapid Build-Measure-Learn process, with the integration of feedback in the form of easily updateable value fields. Therefore the experimental focus of the canvas is ensured, and the emphasis on the easy-to-create value representations is highlighted. What is more, this experimental, and therefore practical, usable approach is seen in the value categorization within the VPC method. The Canvas does not ask the developer / customer for a set of highly imaginative, out-of-ordinary values. Rather, the priority is given to the Values-in-Use, and therefore their practical implications. What is more, VPC emphasized the placement of values within the hierarchy of user practices and realizable product features, ensuring their connection to real-life application. Early stage startups focus on the MVP and look for a way for a first sale, hence the attention towards the usability is beneficial. The Value Proposition methodology of the VPC is established on the exploration of feasible value sets, obtained by asking open-ended questions that guide the business developer. By focusing on the most often found notions of unique value development, the VPC helps explore the potential product advantages in a universal manner.

Although the Value Proposition Canvas has significant benefit and offers an advantageous methodology for the discovery of potential product and service values, it lacks in establishing of certain features that are favorable in an effective VP process. Despite focusing on the ‘fit’ between the product and customer values, manifested in the direct relationship between the two, VPC lacks a formal way of communicating the values to other actors involved. Although the process is easily understandable and can be used as a background for effective methods of value communication, within itself it does not offer any specific forms or a strategy of delivering the concepts (other than the ‘fit’ itself).

As it has been shown in the literature study of customer discovery, the integration of potential customers into the design process is crucial, if effective value definition and assimilation is the goal. Osterwalder highlights the importance acquiring information from stakeholders and potential clients in a form of interviews and their methodical analysis (figure 4.3. In this way, the business hypotheses can be validated and feedback implemented with the business models. And although the guiding questions for value discovery are very specific and useful, the method lacks a similar approach to the communication methods, which can be equally complex.

Moreover, the VPC bases the value assumptions only on qualitative methods. This approach is not incorrect per say, in fact can be highly beneficial when assuming high level product definitions. Nonetheless, the lack of qualitative structuring, assessment, and grading of the values may be the reason for insufficient understanding of the true pain and gain points on the side of the customer. Osterwalder proposed a method for the subjective rating of im-

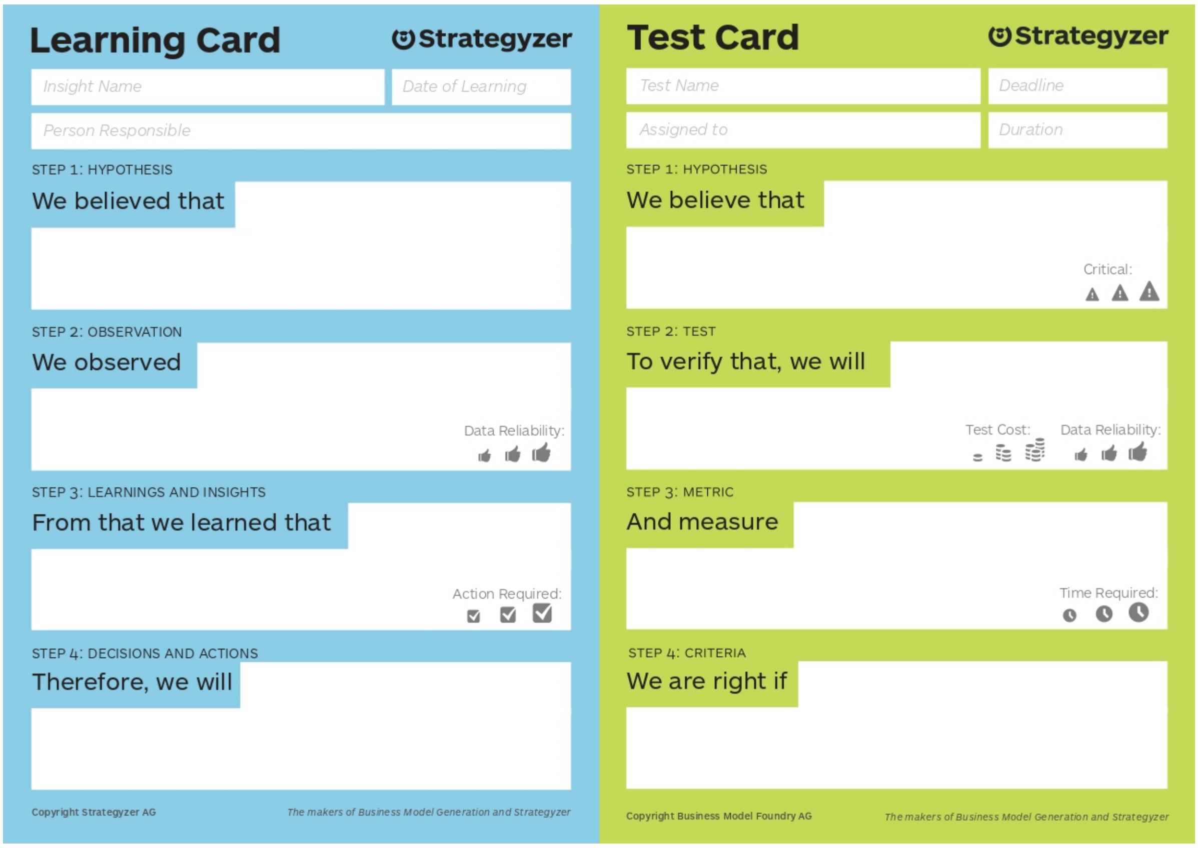

Figure 4.3: Learning and Test cards used in the VPC process (Osterwalder, 2014)

portance, however again it is mostly done without the integration of the customer. It may be argued that such approach may be beneficial in the early stages of the product development, where the idea is to guide the developer towards certain aspects of the process. Still, one can argue that a qualitative, deterministic approach to the value grading may lead to a more consistent VP and effective solution integration.

Stemming from the notions of value communication and quantification is an additional aspect of the VPC that is not substantially considered in the process. VPC does not specifically state the importance of value documentation, representation, and progress tracking. The canvas is the only model that is used for the purposes of indication and information storing. It is argued that the purpose of the VPC is to act similarly to a Kanban board, upon which values are added in the form on *sticky notes*, allowing for quick presentation and ability to change. However, as the customer discovery progresses, it becomes important to store and process this information, especially for further evaluation of the findings. The developers are required to document the findings in a concise manner, however it may not always be directly correlated with the VP framework. This lack of coordination may lead to verification and tracking issues.

Regarding verification itself, VPC does not quantify the fit of the value proposition in any way other than the correlation of pains/gains and their corresponding reliefs/providers. The impact of these relationships is not stated, however the overall effect of these value propositions is studied beyond the conceptual phase. It mush be mentioned that Osterwalder provides methods for value ranking and testing (especially through the BMC). What is more, the synthesis of values, their impact on the realized product is analyzed through customer interviews; Osterwalder provides good practices and ideas, as well as step by step methods of feedback integration. Testing business hypotheses is well structured in the documentation describing the framework, and the general premise is “The faster you iterate, the more you learn and the faster you succeed” (Osterwalder, 2014). There is a strong emphasis on the hypothesis verification through iterative customer interviews, however a verification method for this data input is not clarified. Yet again it should be realized that VPC is primarily a quickly deployable, iterative method for value proposition, and combination of too many aspects within its framework would be excessive. The issues of value communication, quantification, documentation, and verification should be considered as pointers by the business developers; certain notions that they could pay additional attention to.

The Value Proposition Creation model can be considered as a value-focus approach to definition of the set of unique product benefits through which competitive advantage is obtained. Although the method relies on the definition of the Customer Map, and subsequent analysis of the pains and gains, VPC does not directly define the way, in which the customer is being researched, selected, and chosen. The framework and its supporting documentation go into significant detail of the information acquisition process, key takeaways, and good practices. However, what seems to be missing is a method for establishing and continuing cooperation with the stakeholders and potential clients. Literature review shows that aside of identifying and obtaining a means of communication with a client, a certain degree of involvement and interaction has to be sustained, each with different tasks and goals.

4.3. Value Proposition in the context of business operation

Based on the assessment of the common practices of the Value Proposition (and Customer Discovery, in parallel), it becomes necessary to understand the relationship of these processes within the context of the entire business operation. As such, it is often placed before the process of Value Creation, which defines the total additional benefit created in transforming the potential client's input to output. (Velu, 2018) Value Proposition Creation is only one of the ways of defining and communicating the solution benefits with the potential clients.

From the perspective of the entirety of the business operation, we can define the three main states that deal with the product value. These are: Value Proposition (which's definition has been given previously), Value Creation (referring to the total additional benefit created in transforming the input to output), and Value Capture (referring the ability as a business to 'capture' that value as the retained profit). This relationship can be seen in figure 4.4.

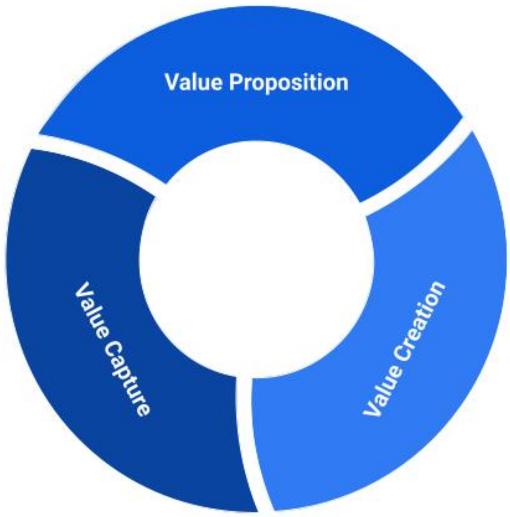

Figure 4.4: Representation of the circular nature of the value proposition, creation, and capture (Velu, 2018)

The value proposition process can be placed before the value creation, which concerns the realization of the previously assumed values for the designated customer. Therefore, the product adoption factors are directly related to the models used for solution creation, assessment of feasibility, and assurance of solution compliance. Nonetheless, because of the intrinsic complexity of the Artificial Intelligence solutions, it may be worthwhile to assess the solution adoption and relate it to the value proposition. The following reasoning may be assumed:

1. Value proposition is an iterative process which looks in depth at the potential customer segments. The customer discovery and subsequent analysis of product-market fit is primarily based on the idea of a 'need' within the customer segment, as it was shown in the literature study. Still, customer discovery methods analyze the product compliance and adoptability from the perspective of the client demand. This demand-driven perspec-

tive must consider the applicability of the solution, ability of adoption, use, and acquiring the necessary benefits. In a similar manner, by looking at the product adoption factors, the developer might be able to assess the proposed value structure and achieve the product-customer fit.

2. Additionally, because of the AI complexity and the aforementioned issues of technology conceptualization, it is difficult to define the unique product solutions without relating it to the reality, in which the solution has to operate. AI solution is a generic term, which can be understood in many ways by both the developer and the potential customer. Therefore, the client may not 'know what they want', as well as the developer may not 'know what to deliver'. An assessment of solution feasibility and applicability already in the stage of value proposition may result in a more effective solution definition and product develpoment.

3. What is more, the vastness of AI makes the value assessment not specific enough. The VP processes have to be realistic, holistic, yet 'need' driven. AI can cover large numbers of problems seen in the potential customer operations, but a good solution focused on a specific problem, and addresses it individually. To assess this problem, the solution developer must be aware of the domain possibilities and limits. The adoption factors may be useful to draft realistic solutions that respond to the particular issues without compromising the product value proposition due to the inability of its application.

5

Empirical analysis

This chapter presents the motivation behind the expert interviews as a means of evaluation of the conceptual framework for the AI solution adoption. Interview methodology as well as their aim and process description are given. In total, six experts in the field of Artificial Intelligence technology were interviewed. The obtained qualitative data is reduced and presented for the purpose of drawing meaningful conclusions. Furthermore, the obtained findings and their impact on the conceptual framework are discussed, and the linking with the value proposition process is established.

5.1. Motivation for the expert interview

Having obtained the conceptual model for the Artificial Intelligence solution adoption, it becomes necessary to evaluate it. Triangulation with another data source is crucial for the reliability and relevance of the research. The analysis of the results from another perspective and by using different methods of data collection enhances the validity, as well as provides additional insights into the studied subject. For this reason, expert interviews were conducted (Triangulation, 2014).

The main motivation behind the expert interviews in this empirical research is to evaluate upon the findings of the literature study that constitute the conceptual model for the adoption of Artificial Intelligence solutions. By consulting and discussing the relevant factors, it becomes possible to judge their individual applicability and interrelationship. This type of data collection also brings additional insight of the studied matter from the actors directly responsible and involved in its course. Furthermore, expert interviews enrich the exploratory studies by bringing in details relevant to the examined domain that would otherwise not be uncovered.

Additionally, the goal of the AI expert interviews is to define the link between the value proposition of an AI product/solution and its adoptability. Because of the preferred interviewee selection process, which assumed the choice of AI experts proficient with the theoretical and practical approaches towards its applicability across several varying fields, it becomes possible to distinctly indicate the particular aspects that are relevant to AI adoption and use.

Other relevant aspects specific to the Artificial Solution adoption can be explored and investigated with the experts. Their personal expertise in the particular fields allows for definition of varying approaches, problems and obstacles, as well as strengths and benefits. The factors presented in the conceptual model may not always be present, moreover their weight and impact may differ. Therefore, by using the interviewee experience and examples from their particular domains, a more thorough understanding of the AI adoption can obtained, which is notably useful for the universal artificial intelligence value proposition.

Interviews are an effective method of primary data collection. This method of data collection is also particularly suitable, when conducting exploratory research. Personal interviews have been carried out among experts in the field of artificial intelligence applications, either face to face, or via a video call. With this kind of data collection approach, rich, qualitative data can be obtained, while ensuring a high degree of internal validity with a significantly high response rate. Moreover, interviewer is able to clarify doubts and reevaluate certain points, as well as use special visual aids (in this case, the conceptual framework for AI solution adoption was presented).

Semi-structured expert interviews have been chosen as the data collection method. This type of interviews bridges the gap between a structured and a fully open interview approach. It provides a certain form and direction of the questioning, therefore allowing for guiding the discussion and obtaining information in particular fields. What is more, the goal of the interview is to evaluate and confirm the findings behind the conceptual model. Hence, a certain imposed perspective is needed. On the other hand, the open aspect of the interview creates means for exploration of the peculiarities and insightful observations otherwise impossible in the strict, controlled interview environment. The interviewee is able to provide additional details, point out specific cases, and contribute their personal experiences, adding further dimensions to the rich empirical data.

5.2. Interview method and process

First, the data collection objectives have been stated. The empirical analysis in this thesis assumes the verification and evaluation of the conceptual model for the adoption of the Artificial Intelligence solutions. Therefore, the primary aim was to check if the list of the factors involved in the process is exhaustive, if there are any crucial factors missing, and if any should be removed or rephrased. In this way, the consistency of the model could be assured. Moreover, the factor grouping had to revised from the perspective of the compatibility of the factor interrelationships. Secondly, the intention was to inspect the relevance and importance of the specified factors from the experts' perspective. The intention was also to look for a notable mention among the factors, or state any mediating or moderating variables.

Simultaneously, the underlying objective of the empirical analysis was the understanding how the AI adoption model impacts the overall value proposition of the technology. The method for structuring the questions was based on the Value Proposition Creation approach. From a practical standpoint, the VPC process was reconstructed and inverted. The method therefore assumed the existence of the values in the first place – defined as the factors responsible for successful AI solution adoption, and exploration of the motivations, goals, pains, and needs that resulted in the AI adoption. In this way, the primary procedure of the Value Proposition Creation has been transformed to allow for the research of the user / customer requirements and the AI solution developer goals.

In order to achieve the goals of the empirical analysis, a specific group of AI experts was chosen for the interviews. The main criterion for the interviewee selection was a high level of competence in the field of Artificial Intelligence application. Moreover, the role definition went beyond AI developer or AI application user. In order to improve the reliability of the research, the interviewee had to have a thorough understanding of the particular Artificial Intelligence technology, as well as expertise in the application and use of an AI solution. It was assumed that a response from a strictly technological or user perspective could be biased towards the respondent's individual experiences, goals, or needs. Moreover, experts from various fields of application – cybernetics, construction management, biomedical sciences, communication – were chosen. In this way, the internal validity of the model was improved, as it was possible to review the same concepts from several angles. University professors and researchers specializing in AI applications were approached and asked to participate in the semi-structured expert interview for the purposes of this study.

When creating the interview questionnaire, the questions seen in the Value Proposition Creation method for the value research were used as a guide to structure the interview and reverse the value proposition process (Osterwalder, 2014). When considering the operationalization of the conceptual framework, objective construct definitions were used, hence each question referred to a single item. In this way, the construct validity was considered. As the intention was to conduct semi-structured interviews, a couple of guiding questions and notes were also made alongside the questionnaire items. In this way, the conversation could have been continued, when relevant or interesting concepts were mentioned. The exploratory format of the interview also allowed for additional personal insights to be made, which could bring in information specific to the field of expertise. Finally, it was ensured that the questions are not leading, ambiguous, or double-barred. Special attention was given to ensuring the lack of social desirability of the researched items, as well as the lack of recall-dependency of the investigated personal expertise. The general framework of the questionnaire used in the expert interviews can be seen in the Appendix A.

For this part of the research six expert interview were conducted. Each interview lasted approximately an hour, covering the questionnaire items and providing additional insights into the concept of Artificial Intelligence adoption. Both face-to-face, and video call interviews were recorded. Every interviewee was presented with a confidentiality agreement (Appendix B). Afterwards, the interviews were automatically transcribed for evaluation, coding, and referencing purposes. Table 5.1 presents the list of experts interviewed in this research.

Table 5.1: List of participants in the empirical analysis - semi-structured interviews

No.	Role	Field of expertise
1	Assistant Professor	Gdańsk University of Technology, Faculty of Electronics and Telecommunications, Department of Biomedical Science; Biocybernetics and biomedical engineering
2	Assistant Professor	Gdańsk University of Technology, Faculty of Electronics and Telecommunications, Department of Microwave and Antenna Engineering
3	Postdoctoral researcher	Amsterdam University Medical Center; Neuroscience with AI background

Continuation of Table 5.1		
No.	**Role**	**Field of expertise**
4	Postdoctoral researcher	Delft University of Technology, Faculty of Civil Engineering, AI application in structural mechanics
5	Assistant Professor	Delft University of Technology ; AI in Structural Design & Mechanics
6	AI Research & Development	Applied Machine Learning and Artificial Intelligence, Delft University of Technology

5.3. Qualitative data analysis

Data collection process created a vast pool of information in the form of video recordings, transcripts, notes, memos, and sketched out ideas. In order to analyze the findings, and make use of the empirical evidence, the qualitative data must be represented in a meaningful way. Data management practices lead to a more coherent and significant structure of the research, allow for direct triangulation, and help form protocols for further investigations. For this reason, data reduction practices were employed for sake of selection of crucial concepts, coding, and categorizing of the findings.

5.3.1. Data reduction

When considering the coding approach, a middle ground between tight and loose method was chosen. A initial thematic list has been formed based on the theoretical findings of the literature study. The code groups have been modified accordingly, as further understanding of the concepts at hand has been gained. Coding has been conducted in three phases. In the exploration phase, relevant concepts have been highlighted, leading to a long list of ideas that represented the findings. During the axial analysis, commonalities and relationships between the codes from the interviews were defined. As the semi-structured interviews followed a certain path, the resulting discussions led to findings in similar, comparable fields. Finally, in the reduction phase, initial categories were revisited and codes have been assigned to the relevant code groups. Table 5.2 presents the code categories and the lists of codes that have been defined in the empirical analysis of this thesis.

Table 5.2: List of codes used in each code group

Code group	List of codes
Data availability	Data sharing, Data types, Data transfers, Predictive models, Information privacy, Big data, Data processing, Data storing, Data & model integration
Integration with other methods	Variability of solutions, Layers of complexity, Human-like process, Decision making process, Operation methods, Planning & prediction, Multimodal solutions
Experiences of the stakeholders	Communication of requirements, Willingness of data transfer, Testing & verification, Intended use, Requirement combinations
Internal capacity for implementation	Computational capacity, Current practices, Technical compatibility, Code availability, Parallel implementation
Previous experience	Coding background, Mathematical background, Statistics, ICT, Data sciences, Automation, Analytics
Perceived costs of implementation	Computation costs, Operation learning, Computation time, Implementation downtime, Data storage, Data security, Testing & Evaluation, Research & Development
Perceived benefits of implementation	Solution improvement, Computation efficiency, Increased reliability, Increased accuracy, Cheaper operations, Realized solution improvements, Quantifiable and qualitative, Custom to domain, Approximation
Differentiation from other solutions	Predictive accuracy, Non-observational, Decision driven, Pattern recognition, Self-improvement, Self-reliable
Organizational agility	Adaptability, Solution absorption, Performance tracking, Issue mitigation, Value capture, Reshaping of operation methods, Responsibility
Organizational structure	Technical support, Theoretical understanding, Comprehension of system dynamics, Domain comprehension, Business operation, Digital transformation
Technology / innovation awareness	Reshaping innovation process, New possibilities, Super-Intelligence

Continuation of Table 5.2	
Code group	**List of codes**
Leadership support	Leadership encouragement, Action coordination, Method explanation, Information modality, Logistics overview, Stakeholder interactions
Trust in AI solutions	Data privacy, Understanding of the algorithm, Explainable solutions, Verification, Solution comparison
Bias in AI	Consensus, Validation, Reflection, Understanding of repercussions
Moral, ethical, and social concerns	Replacing humans, Approximation of error, Bias, Responsibility, Poor understanding, Discrimination, Favoritism

The reason for the generation of the list of codes under the relevant code categories was twofold. Primarily, it was noticed during the literature study that the particular aspects of the factors influencing the adoption of AI solutions can be directly translated into the product's Value Proposition. Through the evaluation of the specific aspects that might be responsible for the success (or lack thereof) in the AI solution adoption, individual product benefits can be highlighted in the VP design process, and solution weak points can be directly addressed. Hence, the list of codes may aid in the assessment and preparation of the AI solution Value Proposition. Secondly, literature pointed to certain relationships between the categorical factors. For example, the 'Data availability' could be related to the 'Organizational structure'. Therefore, one of the interviews' goals was to try to establish these relationships, and a clear understanding of the underlying causes and elements is vital.

5.3.2. Data representation

The exploratory experts interviews generated a large amount of knowledge and insights. Because of the varying backgrounds of the AI experts, rich data was obtained. It allowed for deepening of the understanding of the processes underlying the adoption of AI solutions. To present the findings, first a thematic network is introduced in figure 5.1. It presents the general research themes and code groups, together with the codes obtained from the interview transcripts.

Moreover, not all of the factors seen in the conceptual model were always specifically

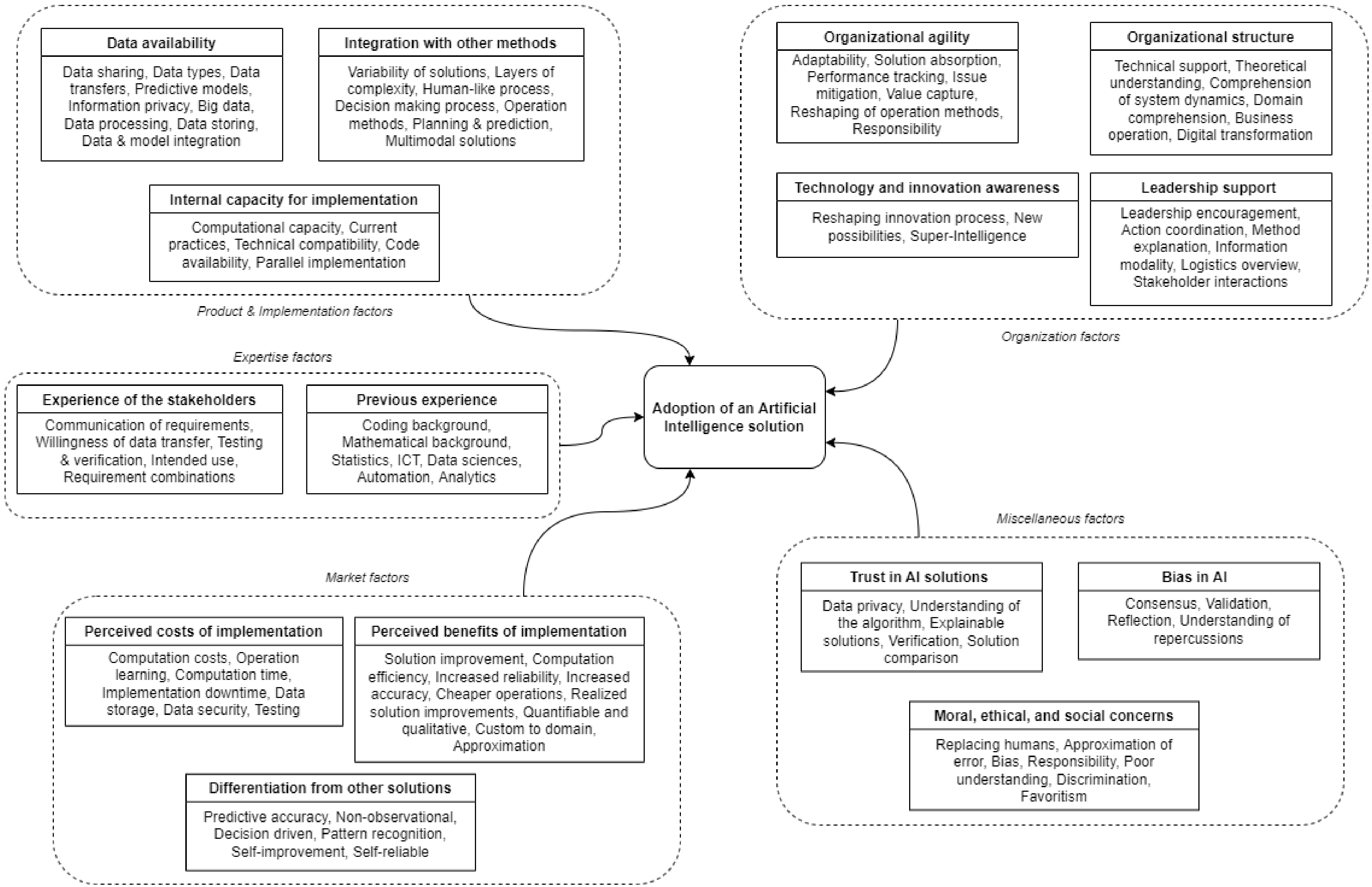

Figure 5.1: Thematic network, presenting the general research themes and code groups with specific codes obtained from the semi-structured expert interviews

addressed by the experts because of the semi-structured nature of the interviews. This is because the format of the conversation had sometimes led to an in-depth discussion of certain aspects of the AI adoption model, or the expert lacked the knowledge or individual examples for the particular field. Nonetheless, the model – including the individual factors and groupings – were directly evaluated with the interviewees afterwards. At this stage, no objections were made to the quality of the model, or the reasoning behind the factor description. Table 5.3 shows which factors in the AI adoption model were categorically mentioned and evaluated by the individual respondents.

Code category	*Expert 1*	*Expert 2*	*Expert 3*	*Expert 4*	*Expert 5*	*Expert 6*
Data availability	●	●	●	●	●	●
Integration with other methods	●	●	●	●	●	●
Experience of the stakeholders	●		●	●	●	
Int. capacity for implementation	●	●	●		●	●
Previous experience		●	●	●	●	
Perc. costs of implementation	●	●	●	●		●
Perc. benefits of implementation	●	●	●	●	●	●
Differentiation from other solutions	●	●		●	●	●
Organizational agility	●			●	●	●
Organizational structure	●		●		●	●
Tech / innovation awareness	●	●	●	●	●	●
Leadership support	●		●	●		●
Trust in AI solutions	●	●		●	●	●
Bias in AI		●	●			●
Moral, ethical, and social concerns	●		●	●	●	

Table 5.3: Semi-structured expert interviews - indication of relevance of specific code categories

Additionally, one of the goals of the expert interviews was finding the individual relationships between the AI adoption factors. The reasoning behind this was to establish possible connections and interdependencies, which could be further used to understand the conditions necessary for successful AI adoption, as well as point towards the vital aspects of the Value

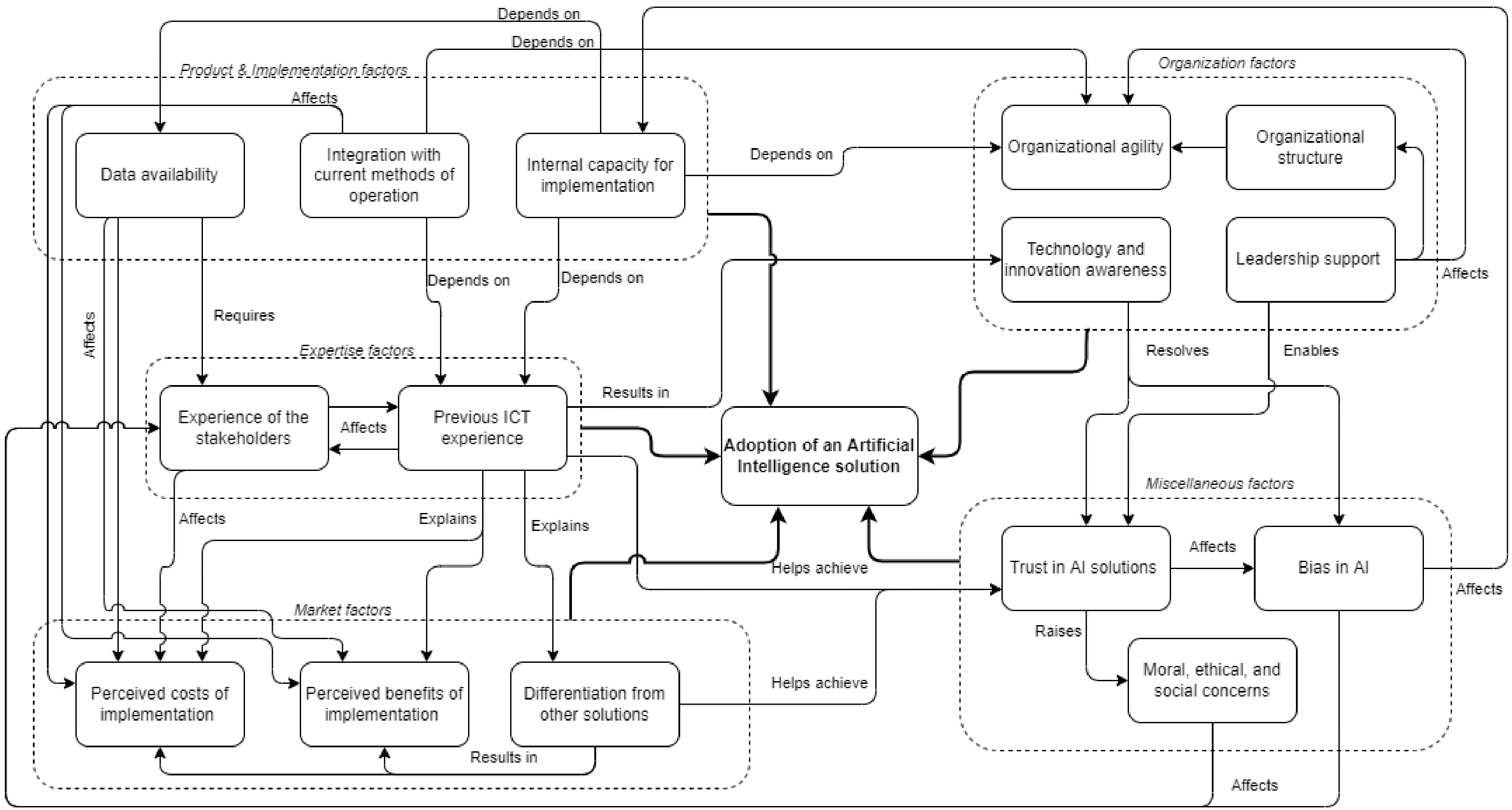

Figure 5.2: Thematic network, showcasing the relevant relationships between code groups

Proposition processes for Artificial Intelligence solutions. Figure 5.2 presents the thematic network, showcasing the relevant relationships between code groups.

5.4. Results of the empirical analysis

To begin the description of the results of the semi-structured interviews, some insight is given into the mutual understanding of the term *Artificial Intelligence solution*. The AI solution can be understood as a tool to analyze large, complex data. Also, it can be a diagnostic, or a decision-making method that is made to be as accurate and precise as possible. Furthermore, the AI usability is one that cannot be achieved through traditional techniques. It may be seen as a metamodel of the real world based on data or models that is able to predict the future, and generate new realities based on its input. Artificial Intelligence can also be viewed as a high order thought process and out way of giving the computers the ability to think.

In order to structure the interview results, the presentation of the assessment is divided into the thematic groups. In each of the groups, particular findings are presented, together with relevant expert statements.

5.4.1. Product and Implementation factors

Across all the domains that were studied in this research, data availability, its quality and transferability plays a major role in the AI product implementation. Because the AI solutions are largely depended on data processing, this lack of AI 'building material' may be the sole reason deciding upon the adoption project outcome. In some cases, relevant synthetic data can be generated via mathematical models. However, in order to adapt the solution to the user requirements, integrate with methods of operation, and ensure high degree of efficacy, the use of real life data is consistently required. Additionally, one of the key features of AI applications is its ability to effectively operate across distinctive data domains. Therefore, the adaptations of qualitative data might be needed.

> *"AI can deal with large amounts of data. We as humans do not have the cognitive capacity to deal with very high dimensional data – because of the ways we had evolved as the species. AI has the incredible capacity to work with big data and distil and recognize patters in this data and use this information to make decisions. Another thing that AI can help us with, especially in the decision-making domain – which in my opinion is one of the most exciting parts of it (...) – it can help us*

> *define a strategy to solve a problem. In this case AI can help us scale very high dimensional systems."*
>
> *Assistant Professor, Delft University of Technology*

The factor of data availability is also characterized by the aspects of data security and storage. Some information may be confidential, sensitive, and hence the access and manipulation may be limited. When adopting an AI solution, the clear definition of data sharing and usage must be stated in the earliest stages of project development. Moreover, the type and condition of the input has to be clarified. Many of the Artificial Intelligence applications may work with pre-existing models, i.e. in case of the DRL applications, the use of predictive models as an immediate input is common.

> *"It is important in a great number of AI fields to have the data available, for example the entire concept of neural networks (…), which is train a specific network, a black box, to think as a human brain based on data. But there are fields in AI, such as Deep Reinforcement Learning (…), where you can generate data, or you can let the agent explore arbitrarily different solutions – and this does not have to feed on specific data, but would rather provide a solution based on the learning of its own."*
>
> *Postdoctoral researcher, Delft University of Technology*

The concept of data/model integration is closely related to the aspect of combination of the AI solutions with other methods of operation. Because of their imitation of human-like processing and ability to learn from past experiences, AI solution may be successfully implemented in the fields of decision making, controlling, prediction, analysis, etc. Such products have a high degree of adaptability to the operational environment, hence hybrid solutions, parallel implementation, or top-down oversight over other applications are all viable methods. However, it is seen that the integration of AI systems with dissimilar information application is difficult due to the coordination of inputs. An expert stated that:

> *"You cannot just upload the information to the system and expect to see the results. Building systems that take multiple types of information is a challenge. We distinguish different types of modality: imaging modality, cognitive domain modality, etc. Combining of these into multimodal AI solutions is hard. There is a lot of logistic problems in multimodal AI solutions."*
>
> *Postdoctoral researcher, Amsterdam University Medical Center*

Similarly, there are certain internal capacity requirements that have to be fulfilled for successful adoption of the solution. A commonly stated aspects are the necessary computational capacity and understanding of the current operation practices. The method of implementation is also being mention, often taking the shape of black-box implementation, modularity, and pipeline deployment. Interestingly, aside from the strictly technical aspects that must be taken into consideration, there is a strong link between the AI adoption and tacit knowledge transfers. It seems that not only the quantifiable factors play a large role, the understanding and overview of the issues, being synonymous with proficiency and level of expertise, may determine the realization and efficiency of the AI system.

> *"The technical challenge is not the primary one. Maybe there are other organizational aspects, which you must take into consideration before deploying the AI at a scale. Typically, when you have a commercial entity, (…) the people, who are able to exploit the AI the most are those, who can clearly understand the problem, the AI and understand the value that it delivers – are able to appreciate it and push it forward."*
>
> *AI R&D, Applied Machine Learning and Artificial Intelligence*

5.4.2. Expertise factors

The previous observation leads towards the comprehension of expertise and experience factors. When considering the organizations, where AI solutions were well adopted, the majority of experts pointed towards the necessity of having a strong, IT/ICT background. This is not surprising, as these solutions are most often adopted in the big data environments. Dependable coding expertise well developed analytics also helps in implementation. Moreover, AI solutions are most conveniently realized in domains, where a high degree of automation is favored. Following the example of the tacit knowledge transfers from the previous section, domain expertise and in-depth understanding of the underlying structures and methods of operation is crucial. Without this comprehension of processes that are in the core of the organization procedures, as well as the mechanisms that guide and rule these processes, Artificial Intelligence application cannot be used effectively. This also follows the previously mentioned qualitative factors that must be embedded into the application.

The domain expertise highlights its importance in an another aspect of the AI adoption. Before the solution is implemented, the application robustness, efficiency, and accuracy must be tested and confirmed. Holistic overview of the domain and relevant expertise may aid in the process. While the competent product designer may realize the AI solution with a high degree of effectiveness, certain system intricacies may only be examined with the comprehensive knowledge of all system dynamics and data relationships. During an interview, one of the experts in the field of biocybernetics and biomedical engineering mentioned the following:

> *"The level of complexity of the task can extend the research time that is needed before we can say that the given model achieves 98-99% of classification for this kind of data. Hence the more complex is the problem and the less the data is accessible, the longer it takes to test the solution and proceed with the next step, which is to implement it."*
>
> *Assistant Professor, Gdańsk University of Technology*

Again, the matter of data availability, quality, and transferability was mentioned in that case. On top of subject, another essential factor was specified. Oftentimes, the data / models are not owned by the organization, that is adopting the Artificial Intelligence solution. The situation emphasized additional expertise factor, namely the level of expertise among stakeholders. Because the realized solutions affect the organization's way of operating, a certain level of actor expertise and subsequent involvement may be involved in the adoption process. As an example, it might be the case that the 3rd party actors will have to readjust their methods of operation. The AI's active character and ability to search for data patterns, optimize, and learn from itself often changes the status quo and the way the user and relevant stakeholders perform their actions. In such circumstances, stakeholder's ability to adapt and communicate effectively in the new reality becomes crucial, further complexifying the technology adoption process. Such situation was described by one of the experts in the following way:

> *"If we are talking about an AI system, which makes decisions and prescribes them, then maybe some of the actors will need to change their common practices in terms of how they operate. The reason is – now the decision is coming from an AI system, so you have to be able to be a bit nimble in your operation. What typically happens in organizations or agencies that operate in a traditional way, is that you have a stiff way to make decisions, and an AI system is more adaptive and more dynamic in the decision making process. So if you have an agency that manages infrastructure, maybe the common practice is that "I will perform maintenance every 5 years, and inspections every two years", and the actors that*

perform the maintenance are tuned in this way of thinking (...), the planning is easier for them. But when you have an AI system, what is optimal is not always the most slow and regular."

Assistant Professor, Delft University of Technology

5.4.3. Market factors

When considering the aspects of the AI adoption that can be generalized as market factors, the perceived costs and benefits are the two most evident ones. The technical costs of implementation can be traced to the scale of the solution, and therefore to the required computational power, accuracy, and instrument calibration. Switching costs often also include the testing and verification of the solutions, as well as the redefinitions of internal operations that have to adapt to the AI ways. As it mentioned before, one of the key strengths of AI is the ability to work in several data domains, including the qualitative procedural aspects. Understanding and encoding these information is not straightforward, and may result in downtime, and therefore additional switching cost. Additionally, the aspect of data appears again in the context of the perceived costs. Data acquisition, transfer, storage, and security may be expensive, especially when handling sensitive information.

Artificial Intelligence solutions can benefit the user by minimizing the required computational power as well as the computational time. These aspects are especially valuable, when considering the big data environments, where operations are complex and thus expensive. AI is characterized by increased efficiency of computation, higher accuracy of results, ability to reach optimal solutions unattainable by conventional computational methods, and customizability, adaptability. Moreover, the realized operational efficiency may affect the created products – by improving the development process, organizations can gain the competitive market edge over the other solutions. An AI expert in the field of microwave and antenna engineering said the following:

"The implementation process can be long – and hence costly – if you don't know what you are looking for and you are not experiences in that field. On the other hand, AI can improve the simulation of measurements, their accuracy, which is an important benefit in the given field. In this way – your solution can be better than the other, and therefore financially beneficial."

Assistant Professor, Gdańsk University of Technology

The other notion regarding the market factors involved in AI acceptance is its differentiation from other available solutions. Artificial Intelligence products can be categorized as self-reliant applications of mathematical procedures that on their own may not be coherent or understandable. Notably, the self-reliability can be recognized in the lack of necessity of constant data input; the AI operations are not purely observational. Compared to other methods, AI is able to recognize schemes, interpret them, and based on the pattern recognition make cognizant decisions. These systems do not always require a constant input of data, and are generally more dynamic. A useful analogy was mentioned, where conventional computational techniques were compared to a traditional, physical map, where individual roads and path have to be found, whereas AI applications provide the versatility of Google Maps.

What is more, Artificial Intelligence solutions are adaptable, and can be retrained to achieve different goals. Depending on the domain requirements, specific changes in the model can be applied to allow a highly different mode of operation and outputs. When considering conventional methods, these are often made to fulfill a task, or a their variety – nevertheless, they can hardly be readopted to drastically change their actions and goals. In case of the AI, the same model can be accommodated to perform a range of actions, depending on the organization's needs.

> *"The AI, especially the deep learning methods can process the large amounts of data much quicker than other methods. The images can contain a lot more information than for example tabular data. (…) Once you had deployed the solutions – for example age prediction for the sample, you can use the method called transfer learning and train the model again, using for example two hundred new samples. This allows for creation of better models; the same model is being used for different tasks, but is simply trained for a special application."*
>
> *Assistant Professor, Gdańsk University of Technology*

5.4.4. Organization factors

The ways in which the organization, in which AI is implemented, operates affects not only the process of its adoption, but also the matters stated previously, such as the data acquisition, or internal capacity for implementation. It should be remembered that the organizational factors are the ones, upon which the AI solution developers have the least control over. Therefore, their uncovering and understanding should be a priority in the adoption process.

Due to their innovative nature and abilities to reshape the operational methods, AI solutions require a certain organizational agility on behalf of the users. A similar notion could have been seen, when considering the stakeholder expertise factors. Solution adoption, adaptability of methodology and approach, and hence the ability to efficiently capture the values provided by the AI systems is needed. What is more, because of the AI's differentiation from conventional computational methods, new ways of performance tracking, testing, and issue mitigation are needed; the dynamic aspects of the Artificial Intelligence solutions affect the pipelining of the internal processes and alter the attitudes of the users. The increased speed, efficiency, and accuracy of computation do not come without a cost – a certain responsibility must be taken, as rapid changes might occur in the organization operations.

What often follows is a rework of the organizational structure. Such processes have been observed in various cases of the Digital Transformation. The theoretical understanding of the domain has to be translated into the AI system inputs. Similarly, an overall comprehension of the system dynamics must be acquired. As seen in the previous examples, AI systems may involve multiple new data assets and realize multi-objective, complex problems. A holistic overview, and thorough understanding of the AI processes in relation to the system behaviors is a crucial factor, confirmed by all of the interviewed experts. Moreover, certain aspects of the business operations might require readjustment too, as the new techniques and methodologies might reshape the value creation processes within the organization. These factors were summarized by one interviewee in the following way:

> *"(What is needed is) experience and domain expertise, operation knowledge, as this also brings up the issue of objective definition. And you can use the organization to really carefully setup the problem and define the objective you want to optimize. Every failure we will observe in the future will be either from an ill-defined objective – we set it up, but we forget that there is something important we had to put into the system. The AI is the perfect optimizer – it will try its best to optimize this objective, but because of the issue we forgot, the process will take an extreme time that we ill not appreciate. Another issue is a kind of overfitting to a certain data set, or a certain environment. You train the model in a given environment, and then apply it somewhere else without adjustment - and you cannot control it anymore."*
>
> *Assistant Professor, Delft University of Technology*

The problem of model overtraining was also mentioned by another expert. What is more, the expert provided an important insight into AI operation, which eases the adoption process by users:

> *"Often the more data you use, the more accurate the results are. However, the AI network can be overtrained, which is a problem sometimes. Moreover, in some simulations, choosing very inaccurate base functions can impair your approach. In AI the base is chosen itself, so in this case there is no required a priori knowledge which can be very important for an inexperienced user"*
>
> *Assistant Professor, Gdańsk University of Technology*

With all of the new requirements, responsibilities, and necessary adaptations of the organization comes the relevant leadership support, realized in effective coordination and necessary encouragement. The AI implementation could also require more direct and active cooperation with the stakeholders, as seen in the case of data transfers and adaptation of operation methods. Coordination of these actions comes along with necessary understanding of the AI value proposition, and the ability to absorb the offered benefits. Because of the particular ways, in which AI functions, as well as the dissimilarities with conventional computational methods, organization leadership is required to build trust in the adopted solutions, by explaining their methodology. The involvement of several parties, and overall transformation requires new strategies to be laid, which include the integration of new possibilities, risks, and relevant obstacles that can appear along the ways of implementation and operation. These aspects were summarized in a conversation with an AI expert in the field of structural mechanics:

> *"If you want to implement a robust application, something that you can also fix and improve, you need to know the theory behind it. You need technical experts that understand the essence of the algorithm and programming languages - people that can implement the algorithm and use the tools. Also there is a need for people that have the knowledge about the system dynamics, because AI is applied in a given domain. For example, the Artificial Intelligence can be applied as a tool in road maintenance domain. We would need someone who knows what the road maintenance entails, what is logical to model and implement, someone that would know the traditional methods. It is often not the same person that couples these two disciplines. And of course the organization segment, as in any technical project. Leaders being able to coordinate all actions. And managers that are able*

to recreate business operations.”

Postdoctoral researcher, Delft University of Technology

Additionally, technology and innovation awareness is a factor encircling and affecting the previously mentioned organizational aspects. The interviewees highlighted the importance of reshaping of the innovation process. Artificial Intelligence solutions have the potential to radically transform the way optimization and decision making processes are conducted, therefore shifting the complexity of operations to new levels. The concept of Super-Intelligence assumes the ability of the AI to surpass human computational abilities, and according to some experts – in some AI domains these ideas are becoming a new reality. Organization will need to adjust to the new realities and remodel their value capture abilities. Overall, Artificial Intelligence systems bring along a vast number of new possibilities and opportunities that have never been seen before. Nevertheless, AI development and deployment should follow similar strategies that can be seen in other high-tech solutions, hence useful strategies can be obtained by looking at adoption of other technologies in these complex domains:

> *“From what I have seen happen, you do not have an organization around an AI product – you have a team. These teams that develop the AI products are very agile, so that everything is need-based. You identify the problem, you break it down into projects, into work packages, and you ship it off to teams which are very agile and then they deliver a product. So by the time you get to the product and its development you already have a very clear value proposition. The role the organization plays is to bring that clarity to know what product to build, and to know how AI fits in it, what tools are required.”*
>
> *AI R&D, Applied Machine Learning and Artificial Intelligence*

5.4.5. Miscellaneous factors

Similarly to other radical technological innovations, application of Artificial Intelligence solutions raises several questions, which have an influence on its adoption process. Due to their inherit complexity, it is challenging to understand and test their operation, especially by non-technical users. This situation causes problems, when compared to other available solutions; AI seems to be more demanding to verify. This lack of understanding of the algorithm is one of the reason for distrust for the AI solutions. Their non-trivial methodology makes the communication of results with stakeholders difficult. Moreover, because of the AI’s reliance on data, there is the issue of privacy and security. The notions of benchmarking, authorization, and assessment are commonly the most significant methods of ensuring the trustworthiness of a tech product. Experts state that such procedures are still under development, alongside with the AI applications:

> *"When you design the model itself, you to be careful to account for all the errors you have in the data. So you cannot go blindly and provide a very hacky solution, which is going to work ninety nine percent of the time. And how about seventy percent of the time – it is still better than fifty! So having these stringent requirements is also a challenge, it is something that can be an inherent risk. Because if you do not have a sufficient accuracy in your models, probably it is not good if you put it in the field, or an application. But on the other hand, AI cannot be so overtrained and so accurate that it is practically useless for anything else. This balance has to be found in the data and in the model."*
>
> *AI R&D, Applied Machine Learning and Artificial Intelligence*

Additionally, lack of trust, and resulting fear of Artificial Intelligence can be seen on a more individual, personal level. All of the experts mentioned the concerns that people have regarding this technology, and collectively attributed it to the lack of understanding. Generally, there is a fear of AI replacing humans, discrimination, privacy, favoritism. The biases towards Artificial Intelligence can be reduced by a thorough explanation and education of the system workings, similarly to any other innovative technology. From the perspective of the adoption of an AI solution, the inability to comprehend the operation and the repercussions of its use seems to be a major blocking factor, according to the experts.

> *"It is the fear of not understanding what is behind the technology. It is much more easily understandable to trust something when we can see its action and effect on the total course, or the objective of the function. But whenever you only see the solution popping up from the black box, people tend to be more insecure and think that this is something they cannot understand. This is why if you don't know the theory behind, it is something that you struggle to trust at first."*
>
> *Postdoctoral researcher, Delft University of Technology*

However, the matters of AI complexity and trust in the provided solution has yet another dimension. As the Artificial Intelligence applications are vast and complicated, it creates an opportunity for (un)intentional malpractice. Three of the interviewees specifically mentioned this example – the codes that are the backbone of AI solutions are so extensive, and their operations are so intricate, it is very troublesome to spot issues. Again, the notion of validation, understanding of AI and its impacts was brought forward. The experts also mentioned that lack of control over AI does not have to take the form of a rise of the 'self-aware machines' – on the contrary, it may be as simple as overlooking a problem in the system and bearing its costs. This factor is yet another challenge that prevents AI from being adopted by users. Interestingly, it was said by one of the interviewees that the value and benefit of the AI cannot be harvested as long as these intricacies are not dealt with.

> *"(…) Because these pieces of code are so complex, for example – you have a huge open access project – if a malicious actor would change a block of code, or a binary shift would be very hard to comprehend. When you have an extensively used public access library, which is compromised, think of the economic consequences of these events. Because the code is so complex, no one can fully understand it and control it."*
>
> *AI R&D, Applied Machine Learning and Artificial Intelligence*

5.4.6. Interdependencies of the adoption factors

In the process of interviewing the AI experts, some factors showed certain dependencies or relationships with other attributes. Understanding these relationships may allow for a more thorough examination of the way, in which Artificial Intelligence solutions are adopted. Some of these dependencies may have been observed when describing the relevant factor groupings. Other were directly mentioned by the AI experts. The mapping of these co-dependencies can be seen in figure 5.2.

One of the most significant factors overall, namely the data availability for the creation and use of the AI solutions may directly affect the perceived costs and benefits of the solution application. This is because of the necessary expenditures of data transfers, storage, and manipulation, as well as the impact the data provision has on the global perception of the solution benefits. Because in many cases, the data belongs or is gathered by a 3rd party stakeholder, for the application of the AI a certain experience and understanding of these actors is required. Moreover, due to the necessary information processing capabilities, the factor depends on the internal capacity for the solution implementation.

Said capacity for integration heavily relies on the organizational agility, where the more agile and flexible organizations are able to morph and restructure in a more effective manner. Such attitude requires a well-defined structure and leadership support on the side of the organization. This support is also needed, when building trust in the AI solution, and its effectiveness internally. What is more, the biases that can be seen in AI can negatively influence the organizational ability to adopt the solution. Additionally, the previous expertise of an organization, especially in the field of ICT / Big Data can improve its capacity for the AI implementation, as well as the organization's ability to integrate the AI solution with its current methods of operation. These in turn are directly responsible for the way the cost/benefit ratio is perceived.

Both – the domain expertise on the side of the user and 3rd party stakeholder can be co-related. As operations get more and more complex, a certain uniformity of understanding is required. Additionally, the stakeholder experience may be influenced by the biases seen in the AI, a well as the resultant moral and ethical concerns. What is more, it was mentioned by one expert that the more experience an organization has, the easier it will be able to understand the differentiation of the AI product from other available solutions. Finally, as seen in the evaluation of the trust factors, internal expertise may improve the understanding of the AI solution, leading to a higher trust in the Artificial Intelligence technology. Higher technology and innovation awareness, especially in the sense of the understanding of the Artificial Intelligence can also be achieved with the organization's previous expertise. As shown before, it may help resolve the trust issues in AI, as well as respond to its biases.

5.5. Empirical analysis - conclusions

The semi-structured expert interviews generated plenty of insights regarding the ways, in which organizations adopt Artificial Intelligence solutions. They highlighted the notions that can be seen in the implementation process. What is more, by pointing to specific situations and examples, the interviews defined the specific aspects, which has to be considered. From the perspective of an AI developer, knowing the issues and obstacles, as well as the possibilities and opportunities creates a strong basis for generating a plan of approach, definition of goals and needs, and therefore – a specific value proposition.

By considering multiple domains of AI applications, general trends were uncovered. In this way, the adoption model for the AI solutions can be generalized and used for understanding of product implementation in various fields. Obtaining valuable, rich data from the Artificial Intelligence experts ensures a high level of external validity of the model. The downside of this approach is the impaired internal validity – it is difficult to estimate, based on this research approach, the causality and whether additional moderating factors can be seen. Nonetheless, it is argued that such adoption model can be effectively used for the value proposition design purposes – as these processes rely on the overall understanding of the studied notions.

It is safe to assume that additional factors involved in the AI adoption, especially when considering the specific examples of implementation of particular AI solutions in a given domain. The approach in this study points out the fact that such research is possible and that the method can be used effectively for definition of the product value proposition. The following chapter provides the details of the adoption model's relationship with the VP process, with the specific aspects surrounding AI technologies and the VPC methodology.

6

Results

6.1. Impact of the solution adoption model on the VP process

The primary subject matter of this thesis concerns the understanding of the ways, in which solution adoption model influences its value proposition. It is theorized that by recognizing these dependencies, entrepreneurs and solution developers might be able to more effectively detect specific values of the technology derived products, as well as the needs and pains of the potential customers and end users. The motivation from this theory comes the patterns seen in the problem formulation of the thesis (in the form of the literature review), together with the qualitative data collection (conducted via semi-structured expert interviews).

A direct link between the solution adoption and value proposition can be seen. Such approach creates the foundation for a value proposition design adapted specifically towards technology products. By considering the factors involved in the specific solution adoption, entrepreneurs and technology managers can distill the problem areas, which should be addressed by the tech product, highlight the potential obstacles, and define core advantages. The association of the solution adoption and product value proposition is further delineated by the framework proposed by Khan and Bohnsack, 2020, seen in figure 6.1 (Khan & Bohnsack, 2020). There, the model for disruptive innovation adoption by users is split into strictly technical Performance Attributes, and the business driven Value Proposition, Network, and Revenue model. This model shows that the Value Proposition of a given technological solution is directly influenced by its technical abilities and performance, which in turn leads to adoptability. In this particular case, the Value Proposition design is understood as the overall process of technology assessment, definition of its strengths and benefits, and areas of opportunity specifically addressing the domain of implementation.

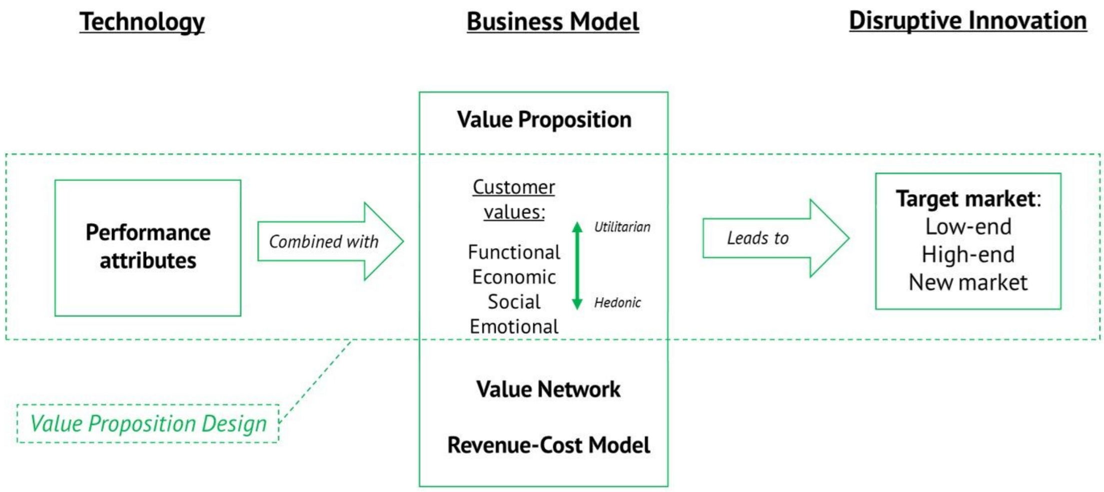

Figure 6.1: The process of value proposition design for disruptive innovations in the context of technology adoption; adapted from (Khan & Bohnsack, 2020)

Specifically in the context of Artificial Intelligence solutions, value proposition definition and design is challenging, because of their categorical dependence on certain adoption factors. By conducting the semi structured expert interviews, it has been noted that there is a strong dependence on quality data provision, user comprehension of benefits, understanding of the employed methods, and integration with other operation methods. This has confirmed the assumption of the existence of essential conditions, which must be fulfilled by the solution developers. While the aspect of increased computational efficiency, decrease of procedure time, optimization of decision-making tasks can be highly compelling to the potential client, missing the core integration and operation requirements may lead to an ill-defined, unfitting value proposition.

Without the proper and thorough understanding of the technology adoption conditions, the definition of a solution's potential values may not be done effectively. Subsequent value communication and capture cannot be realized, if the core product aspects – in the forms of integration methods, solution trustworthiness, understanding of benefits and implementation requirements – are missing from the product's value proposition. Therefore it is argued that a certain number of prerequisites must be considered before providing the AI as a viable solution to a potential client. By following the steps of the AI adoption model, and subsequently acknowledging or implementing these certain aspects into the product, the solution developer may more effectively define and communicate the values of the product that address the crucial notions.

In the context of an Artificial Intelligence university spin-off, this comprehensive evaluation of adoption and integration requirements adds another level of complexity to an already convoluted, and dynamically evolving process of value proposition design. Fortunately, the Value Proposition Creation method can be effectively used in aiding the business and product developers in focusing on the core aspects of the AI adoption. The underlying motivation during this thesis research was to leave the VPC process untouched. The simplicity of use, direct integration with the BMC, and ability to be quickly readapted are the main benefits of this method, hence adding an overlay would mean sacrificing certain usability aspects.

The process of value proposition design for the Artificial Intelligence technologies is challenging because of a multitude of factors. Primarily, the complexity of these solutions and their abilities to reshape and restructure organization's methods can be recognized as the two most significant aspects, which make the process very demanding. The goal of the conceptual model for the AI adoption was to attempt to describe, which aspects that are considered during the adoption process may in fact provide insights into the challenges of AI's innovation and complexity. What follows is a more thorough understanding of what makes the AI adoption process problematic, where the opportunities are, and how they can be ultimately addressed.

6.2. Guiding the AI Value Proposition

The complexity of the Artificial Intelligence solutions makes their unique value proposition challenging. The research showed how the adoption factors can be used for verification of feasibility of an AI product. Nonetheless, the adoption factors themselves do not define the value of a product. As it was shown before, the adoption frameworks are most often used in the context of value creation models, which base their purpose on the well-defined value proposition methods. It can be argued however that the solution adoption factors can be used as a guideline to create a solution value proposition, which are grounded in reality and can be more successfully implemented in the later stages of product development.

Therefore, it is necessary to look at the previously defined adoption factors from the perspective of their impact on the value proposition framework, in the case of this paper – the Value Proposition Canvas. It should be mentioned that the goal is not the edition of the Canvas itself. One of the main advantages of the VPC is its simplicity, repeatability, and agile method of operation. Adding new fields to the VPC seems counterproductive, as it interferes with the methodology and creates unnecessary barriers for the framework usage. The goal of this part of the value proposition research was to define certain questions based on the AI adoption factors that are relevant to the AI solution specific value proposition.

This approach is in line with the VPC method itself. Osterwalder presents the pathway for filling out the individual segments of the VPC by asking multiple questions, which the solution developer answers in a form of value definitions. By examining the Value Proposition Canvas through the lens of common practices found in other methods for value proposition and solution customer discovery, a general awareness of the aspects responsible for a successful framework was obtained. The iterative approach of asking relevant questions as a form of thought guidance seems to work effectively. Therefore, in order to define the VPC for an AI solution, a business developer might benefit from such approach towards the value alignment with the realistic, deployable, and implementable AI features.

Additionally, by reviewing the potential strengths, opportunities, and possibilities of the Artificial Intelligence solutions together with their requirements and challenges, it became possible to formulate several questions that relate the adoption factors to the solution's unique value proposition. It should be mentioned that the answers to these questions are not the values itself. Rather, they allow the developer to define realistic benefits and strengths of the application that have a higher chance of implementation. Because the AI solution developer is encouraged to thing about the product values while keeping in mind their feasibility, the chances for value creation (ergo – implementation) in the real setting and therefore for value capture increase.

The conducted expert interviews provided extensive insights into the AI solution adoption process. Provided answers generated knowledge of the particular adoption variables. The experts provided real life examples, mentioned general trends, and specific cases that they had observed during the AI solution incorporation. This information was then used as a background for the creation of the relevant questions that should be asked during the Value Proposition process. It should be highlighted that the goal was not to modify the VPC as a framework. Rather, the addition of any other elements has to be in line with the VPC methodology and not interfere with the value proposition process.

Each adoption factor that has been recognized in the relevant literature was described with examples of necessary objectives, commonly found items, and other appropriate variables (figure 5.1). These items served as a starting point of defining the relevant adoption questions. The goal of this part of the research was to formulate the questions in a way that is similar to the method of the value guiding questions, stated for the VPC process (Appendix C, D). Moreover, the interviews allowed to draw conclusions on the interrelationships between the adoption factors (figure 5.2). Understanding these relationships helped in guiding of the adoption factors and allocating them on the Value Proposition Canvas (figure 6.2). It should be mentioned that these factors are not the values themselves. Instead, figure 6.2 serves as a guideline for the solution developers. The allocated adoption factors disclose the potential interference, relevance, or dependency of specific value on said requirement.

6.3. Incorporating AI adoption factors into the VPC framework

The following list of questions, relating the individual adoption factors to the process of value proposition can be used as a general guideline:

1. Data availability
   (a) Is there sufficient data available for the operation of the Artificial Intelligence solution?
   (b) Can the data be effectively obtained, transferred, and modified if needed?
   (c) Are there any obstacles resulting from the 3rd party data ownership?
   (d) Are the security challenges resultant from the data handling considered?
   (e) How does the data availability influence the solution value proposition to the potential customer?
   (f) Does the proposed solution require data input before, during, or after development; does it require constant data input for operation?
2. Integration with current methods of operation
   (a) What are the methods of operation the customer engages in?
   (b) How can the AI solution be implemented within the structure of customer's operation?

   (c) Does the AI value proposition reflect upon the features of other methods of operation? Is feature cannibalization avoided?

   (d) Is the customer able to capture the proposed solution values, while engaging with the current methods of operation?

3. Experience of the stakeholders

   (a) In what way will the external stakeholders be involved in the AI solution use process?

   (b) Are the external stakeholders aware of the customer's willingness of AI use?

   (c) Are there concerns among the stakeholders?

   (d) Have the external stakeholders engaged previously in the AI operation?

4. Internal capacity for implementation

   (a) Can the proposed AI solution value be realized within the customers current capacity?

   (b) What changes must happen internally for the implementation of the AI solution?

   (c) Can the improvement of internal capacity improve the value proposition of the solution? (e.g. additional computational power, more data storage)

   (d) What are the aspects of the customer's internal capacity that must be considered for the effective realization of the value proposition?

5. Previous experience

   (a) Does the customer have previous experiences (both positive and negative) that may influence their perception of the value proposition?

   (b) Are there any useful parallels that can be made with the customer's previous experiences that would aid in explaining the value proposition?

   (c) Does the client possess previous experiences that may aid in the realization of the AI value proposition?

6. Perceived costs of implementation

(a) What is the impact of the proposed gains and pain relievers on the perceived cost of implementation?

(b) What are the necessary configurations and adaptations on the side of the customer that would be necessary for the capture of the proposed values?

(c) What are the required analysis and testing procedures of the proposed AI solutions?

(d) Does the value proposition takes into consideration the necessary integration downtime and implementation security?

(e) Is the proposed computation time perceived as valuable to the customer?

7. Perceived benefits of implementation

   (a) Does the value proposition reflect upon the increased computational efficiency and customers' ability of delivering more reliable, quicker results?

   (b) What metrics are used to define the quantifiable operational improvements, and how do these improvements relate to the qualitative aspects of the solution?

   (c) Does the VP considers the solution ability to approximate the results?

   (d) How does the new reliability of operations translate into the proposed solution gains and pain relievers?

8. Differentiation from other solutions

   (a) Are the innovative aspects of the Artificial Intelligence solutions considered as benefits in the value proposition process?

   (b) How different is the proposed solution? Is the value proposition realistic?

   (c) Do the currently used methods of operation be causing the customer pains? Can the switch to AI-based solutions provide a way of mitigating them?

   (d) How does the self-improvement (due to automatized learning) impact the delivered values in the long run? Does the value proposition evolve over time?

   (e) Can the added functionality relief customer pains that are not considered by the current methods of operation, i.e. respond to issues seen in other domains of the customer activities?

9. Organizational agility
   (a) Is the organization agile enough to implement a complex AI solution?
   (b) How can the proposed values be absorbed and realized by the organization?
   (c) Is the new improved performance trackable by the organization?
   (d) What amount of the AI solution value can be captured by the customer? What can be done to increase the value capture?
   (e) How can the operational methods of the customer be modified to implement the solution with the specific proposed set of values?
10. Organizational structure
   (a) Are the proposed values realizable under the current organizational structure?
   (b) Is the set of features of the proposed solution be supported by the technical team of the potential customer?
   (c) Does the business operation have to be transformed in order to adopt the proposed product?
   (d) Can the organizational structure have an impact on the method of delivery of the proposed AI values?
   (e) How will the proposed set of benefits and gains alter the structure of the organization?
   (f) How does the organizational structure respond to the general digital transformation?
11. Technology and innovation awareness
   (a) What kind of gains does the customer expect from the AI solution? What is their perception of the values it will deliver?
   (b) Does the value proposition of the AI product takes into the account the new possibilities defined by the AI solution?

(c) How does the customer segment respond to the innovation processes? What are their methods of innovation adoption, absorption, and integration?

12. Leadership support

    (a) What is the leadership perspective on the implementation of the proposed product?

    (b) Can the value proposition be realized more effectively should the leadership support be increased?

    (c) What issues in the AI implementation can be avoided with the better support from the organization management?

    (d) Has the organization leadership opposed AI implementation before? Would that situation affect the understanding of the proposed gains and pain reliever?

    (e) How are the customer's jobs realized in relationship to the leadership? What is the company structure? Who would be affected by the AI product implementation?

13. Trust in AI solutions

    (a) Are the proposed benefits considerate of the privacy issues resultant from the solution application?

    (b) Does the client previous experience or methods of operation affect their trust in the proposed product?

    (c) Can the unique value proposition be verified to increase the user's trust in the solution?

    (d) How well is the proposed solution explainable to the potential customer segment?

    (e) Can the potential mistrust in the AI solution be the reason for the client's pains in their daily operations?

    (f) Is the algorithm operation understandable well enough, so that the product proposition can be attractive to the potential customer segments?

14. Bias in AI

(a) Does the value proposition creates potential issues with regards to operational consensus or the validation of the results?

(b) How does the value proposition deal with the understanding of the repercussions of the proposed features and benefits?

(c) Do the potential clients' pains affect the bias towards the AI solution?

15. Moral, ethical, and social concerns

    (a) How is the proposed solution perceived by the potential user? Are they aware of its operation?

    (b) Do the moral and ethical concerns affect the proposed value of the product?

    (c) Does the VP process assume these concerns and is aware of ways to mitigate them?

    (d) Does the VP avoid favoritism and discrimination?

    (e) Is the unique AI Value Proposition understandable to the users, clients, and stakeholders?

6.4. Value Proposition Creation for Artificial Intelligence solutions

The questions that consider the adoption aspects of the Artificial Intelligence solutions can be related to the particular fields of the Value Proposition Canvas. It should be noticed that the answers to the adoption-related questions do not define specific values that can be linked directly to the VPC. Rather, they act as guideline, an aid to answer the VPC-related value questions. Sample questions that can be used directly to define the product values can be seen in the Appendix C, D. Clearly, they offer a general understanding of the points of interest that should be looked upon during the product value definition.

Still, the intrinsic complexity of the AI solutions imposes a major challenge on the process. Should the solution developer base all of their value presuppositions for the AI only on the answers to the questions from the Appendix C, D, the resultant Value Proposition would be too broad, general, and would contain the specific aspects that are relevant and crucial to the realization of the AI solution. This complexity requires a certain attitude towards the product Value Proposition Creation, particular specificity that relates the strengths, obstacles, and challenges to the unique Value Proposition for the AI. On the other hand, the Canvas is a tool which's strength is the simplicity and quick usability, hence any major modifications would kill the purpose and its agility. For this reason, the AI adoption questions can be related to the individual fields of the VPC. By studying the adoption potentials and challenges in the literature evaluation and during the empirical study, certain relations were noticed. These relationships have to do with the impact that the adoption factors have on the unique AI value proposition.

To achieve a more usable tool, an understanding of the association between the conceptual adoption model and the VPC is needed. This was achieved by analyzing the potential answers to the solution adoption questions and the impact / correlation they might have on the specific VPC fields. What must be remembered is that the adoption factors, nor the answers to the adoption questions are not specific AI solution values. They act as checkbox, a method for verification of the proposed benefits and gains. In this way a more coherent, robust, and grounded in reality Value Proposition for the AI solution can be created.

Therefore, the intention behind this research becomes finding out in what ways can the Value Proposition Creation process can respond to the challenges and opportunities in the Artificial Intelligence solution adoption. The VPC provides a simple methodology that can be regulated and managed so it allows for the definition of specific values of the AI solutions that acknowledge and cover the notions seen in the implementation process. This is especially useful from the perspective of the university spin-offs and startups that may lack sufficient technology research capabilities.

For this purpose, let us reconsider the individual fields in the Value Proposition Canvas. By understanding the reasoning behind this methodology, it becomes possible to evaluate the findings of the adoption model, and assign the particular AI adoption factors to the given subgroups. This in turn may help the business and AI developers to guide the value proposition design so that it responds to the customer needs, fills a niche, and brings out the product benefits in an optimal manner.

6.4.1. Value Proposition within the VPC model

Considering the definitions of the relevant value subgroup in the VPC model, it becomes possible to align the previously obtained AI adoption factors with the Canvas. By representing the particular aspects that fall into the categories on the relevant adoption factors, we can evaluate the impact that they might have on the value proposition of an AI product. This process is very general – similarly to the Value Proposition Creation. With that said however, such approach might enable the developer to consider the specific aspects of the proposed solution in face of the requirements that a successful implementation might require.

When evaluating the Gain Creators of the Artificial Intelligence solutions, the perceived benefits and costs of implementation should be taken into consideration. The primary motivation behind this set of value proposition from the perspective of the VPC is the communication of possible profits and benefits resultant from the AI application. Therefore, the cost/benefit analysis plays an important role. Moreover, the actual differentiation of the solution improvement, statement of improved computational efficiency, reliability, and accuracy are truly necessary. Similarly, the factor of the internal capacity for implementation relates to the solution's Gain Creators. Current practices, methods, and overall capacity for implementation should be taken into the account, when providing a solution. Lastly, the level of expertise – both on the side of the organization as well as the 3rd party actors – may influence the gain value proposition. This is because the relevant technical background and experience may have an impact on the general understanding of the solution and therefore on the possible value capture.

From the perspective of the Pain Relievers, ability to integrate the solution into the organization's method of operation may help address the specific pain points the potential user might have. By analyzing and evaluating upon these pain points, developers may create a product more suited towards a distinct application. A similar relationship can be seen with the factor of differentiation of the AI from other available solutions. Here, by examining the alternative approaches, strong points for the AI's ability to fix underperforming solutions and eradicate errors and mistakes of other applications can be stated. On the other hand, the internal capacity for implementation also plays a role in the Pain Relievers definition. This is because the user's ability to implement and effectively operate the AI system has to be considered and reflected in the method of addressing the potential improvements to the status quo.

The final segment of the VPC's value map addresses the offered Products & Services. In case of the Artificial Intelligence application, the most crucial and critical aspect affecting this group of values is the data availability. As seen during the empirical analysis, model and data availability, data sharing and processing are oftentimes the most decisive factors, when considering the adoption of the AI solutions. It can be said that without data there cannot be Artificial Intelligence. Therefore, the entirety of the products the developers can offer, their functionality, services, abilities are ultimately dependent on the available data. This highlights the importance of consideration of the information exchange, especially in the beginning of the adoption process, when the solutions and systems are being constructed. The integration of the available data and models de facto creates the AI solution, hence the package of products and services offered heavily rely on them.

6.4.2. Customer Profile within the VPC model

The same approach of AI adoption factor assignment can be used in the context of the Customer Profile. When considering the particular gains that would satisfy the potential customer, the factors of perceived benefits and costs of implementation again play the major role. The user looks for particular solution improvements, higher efficiency of operation, and financial gains. On the other hand, the customer always checks the costs of realization, operation, additional training, etc. Therefore, from the perspective of AI adoption, it becomes necessary to include that notions in the customer profile. Not only may be potential client not be aware of these costs, because of the AI reliance on data and preexisting models, these costs may be hidden, difficult to spot instantly. What is more, the clients technology and innovation awareness may shape their willingness to implement innovative solutions and benefit from their possibilities.

Likewise, the analysis of customer Pains revolves around the difficulties and challenges that are currently unresolved, as well as the possible risks and fears. The primary question that should be answered, when evaluating the factors defining the customer Pains is – what keeps them up at night, what are the main issues, concerns, and worries. Therefore to understand these notions, a thorough analysis of the current methods of operation should be conducted. What follows is the understanding of the impact of integration of AI with other methods of operation, as well as the differentiation from other solutions. Similarly to the Pain Relievers in the Value Map, these aspects should be recognized in the potential clients. Additionally, the aspects of AI bias, trust in said technology, and resulting moral, ethical, and social concerns have an impact on the client pains. These factors may not necessarily be directly resulting in customer pains, however they definitely may influence the customer perceives the ability fix under-performing solutions, or eliminate the involved risks. Moreover, because this segment focuses on eliminating the barriers that are keeping customers from adopting value propositions, the issues of trust, bias, and concerns must be taken into consideration.

Finally, the Customer Jobs looks primarily at the different contexts that the customers might be in, their goals and activities that change depending on these contexts. Considering this, from the perspective of AI adoption it is necessary to include the factors of organizational agility and structure, and the leadership support. By analyzing these aspects, it becomes possible to understand how the organization operates and what it needs to accomplish that involves, especially with interaction with other stakeholders. Considering the examples of data sharing and inter/intra organizational communication, a perception of the client's methodology, its adaptability, and coordination is vital for establishing an AI product. Moreover, by track the customer's interaction with a product or service throughout its lifespan, it enables the developer to comprehend the supporting jobs that surface throughout this life cycle, therefore tailoring the solution to the particular needs of the client.

The factors responsible for the Artificial Intelligence solution adoption can therefore be placed on the Value Proposition Canvas, as a guideline for the design process of the specific AI Value Proposition. These groups of factors and their corresponding sub-factors, derived from the expert interviews, are not necessarily meant to be understood as AI's values, or benefit. Rather, they form a certain protocol, a pathway for the AI business developers. By referring to these crucial aspects, it is argued that a more effective, holistic, and inclusive Value Proposition can be constructed with the use of the Value Proposition Canvas. Figure 6.2 presents the Value Proposition canvas by Osterwalder, 2014 with the relevant AI adoption factors, as a visual representation of the aspects involved in the AI Value Proposition design.

6.5. AI Value Proposition Creation - recommended practices

The abovementioned placement of the Artificial Intelligence adoption factors on the Value Proposition Canvas is one of the ways, in which the value proposition can be designed for AI application. Additionally, it is important to reflect upon the methodology presented in the VPC with the consideration of the previously stated evaluations of this VP technique. By doing so, a clearer picture for the VPC for AI solutions can be obtained, which includes appropriate practices specific to the notion of AI implementation.

Using the previously mentioned framework for comprehensive value proposition development (Payne et al., 2020), together with the observations made in the field of customer discovery, as well as the overall evaluation of the Value Proposition Creation, it is possible to highlight key actions and fundamental goals that should be reached in the value proposition design. Simultaneously involving the specific aspects of the VPC for AI seen above, we can construct a step-by-step methodological approach for the value proposition in the context of Artificial Intelligence that involves the intricacies resulting from the AI adoption processes. The overview of these key points is presented on the figure 6.3.

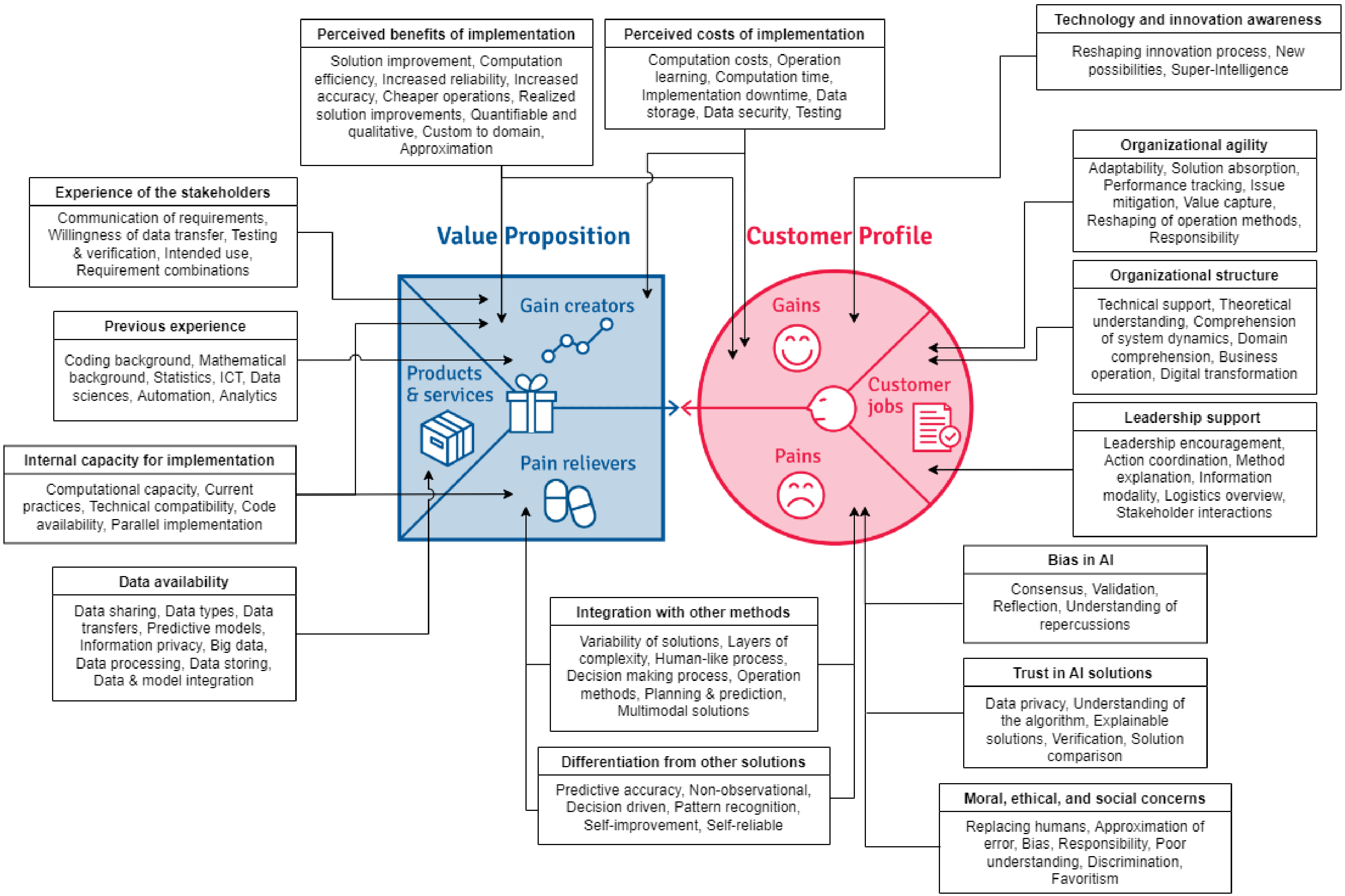

Figure 6.2: Placement of the relevant adoption factors, including the particular codes obtained in this research, on the Value Proposition Canvas

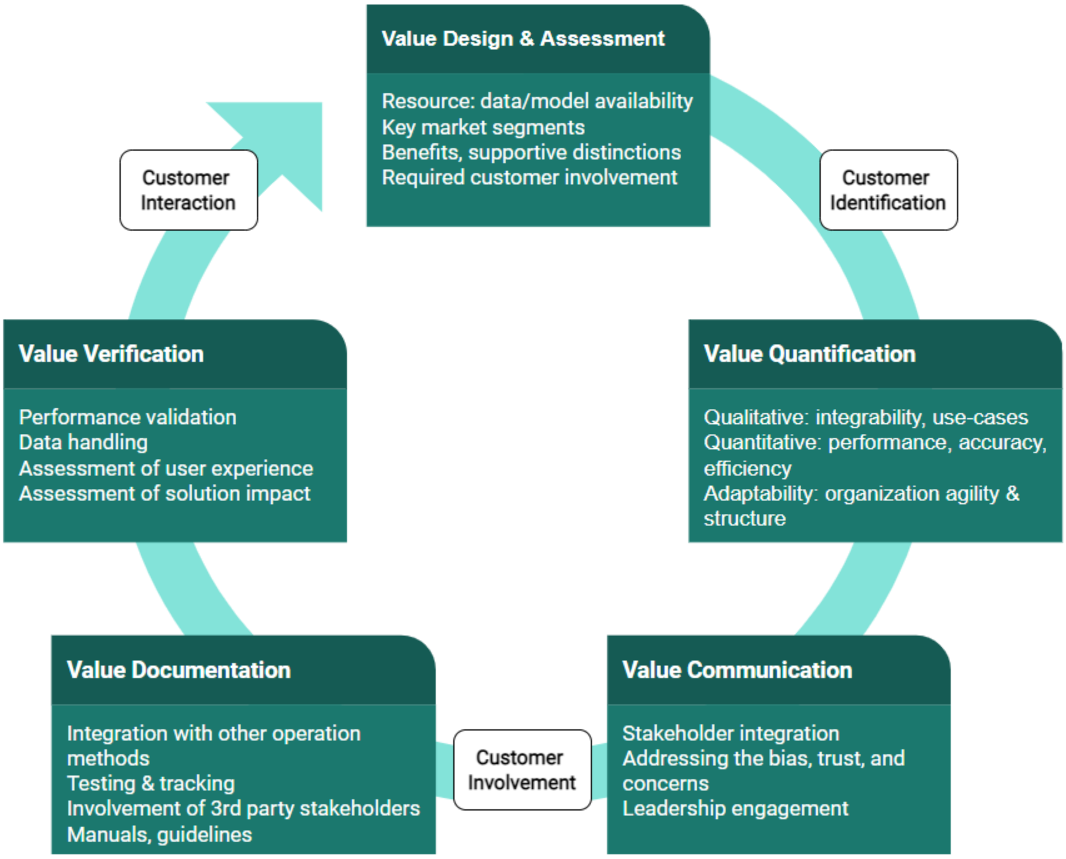

Figure 6.3: Evaluation of the practices found in the Value Proposition Creation for Artificial Intelligence, using the Value-in-Use framework (Payne, Frow, Steinhoff, & Eggert, 2020)

1. **Phase 1: Value design and assessment** The primary step in the value design is the assessment of data and model availability for the purposed solution. Based on these findings, it will possible to draft the potential Gain Creators and Pain Relievers, once the customer needs and goals are uncovered. Moreover, it is important to estimate the level of involvement of the customer and 3rd party stakeholders. These steps should lead to a customer identification for further exploration of potential benefits of the solution.

2. **Phase 2: Value quantification** In this phase, the assessment of solution integrability with the customer's modes of operation, based on specific use cases should happen. Moreover, the quantitative aspects, such as desired system performance, necessary accuracy, and goal efficiency must be stated. When looking at the adaptability of the solution, as well as methods for product implementation, it is crucial to include the organizational agility and structure, so that the assumed method is effective.

3. **Phase 3: Value communication** In this phase, addressing the biases towards AI, building

trust, and resolving concerns has to be the priority. What is more, this approach should include the relevant stakeholders that can be affected by the AI solution adoption. Value communication should also be realized with a high degree of leadership engagement, as this factor influences the ways, in which organizations build confidence in AI solutions. What is more, this phase of value proposition should lead to a more pronounced customer involvement and establishment of necessary feedback loops.

4. **Phase 4: Value documentation** Value documentation should specifically mention the integrability with other methods and applications, as well as the data and model dependencies of the proposed solution. Because of the AI's distinct ways of operation, testing procedures and performance tracking has to be reestablished, and mechanisms for the proposed value assessment have to be created. Moreover, 3rd party actors and other stakeholders have to be considered in the value documentation process. Manuals and guidelines should include the solution aspects necessary for the realization of Gain Creators and Pain Relievers.

5. **Phase 5: Value verification and Value Proposition review** The beginning of the verification must lead to the customer interaction and therefore the assessment of the product use. Performance tracking has to be realized according to the previously assumed methods. From the AI perspective, it is important to verify the data handling processes: transfers, storage, manipulation – as these aspects may be beyond the developer's control. Also at this stage, the fit between the Value Proposition and Customer Profile of the VPC should be established and evaluated with the client. By analyzing the AI solution impact, it becomes possible to highlight the necessary product features that are required by the client for the value capture and product integration.

7

Exploratory case study: DRL implementation

7.1. Case study introduction

A single exploratory case study has been performed. The case considered the application of Deep Reinforcement Learning algorithms as a decision-making tool in the field of inspection and maintenance on the Dutch road network. By examining an actual case, more insights can be obtained on how the proposed framework for AI Value Proposition functions. The research explores the particular aspects that may affect the Value Proposition of the DRL application, and attempts to extrapolate the individual values and benefits, which could be found in this given scenario.

7.2. Background and motivation

7.2.1. Problem context

It can be said with a high degree of confidence that our outlook on automobility, especially on the innovations that emerge within it and because of it, has changed and severely complexified in the last two decades. Rather than looking at a car as an individual manifestation of our need to commute and travel, a more systemic approach is of great value. Proposed by John Urry, the 'System of Automobility' (Urry, 2004) provides an insightful methodology that highlights the importance of other elements constituting said structure. Likewise, the socio-technical perspective for automobility, as defined by Frank Geels, creates a multilevel, heuristic framework for the analysis of niche and regime interactions (F. W. Geels, Sovacool, Schwanen, & Sorrell, 2017). We can conclude that transportation based on the automobile is still effectively dominant and stable. Nonetheless, moderate cracks in the regime are visible, from which windows of opportunity for innovation emerge.

However, system stability, whether definitive, or apparent (e.g. caused by technology lock-ins and industrial sunk costs (Farla, Alkemade, & Suurs, 2010)) may just as well be temporary. Moriart, Honnery (Moriarty & Honnery, 2008) and Jeekel (Jeekel, 2015) point out the fact that car ownership as well overall vehicular travel will continue to rise. The notion stands in direct opposition to the concepts of peak travel and peak oil (Goodwin, 2013) that de facto define measures blocking further expansion of the system. These notions seem intuitive and obvious – we can only have so many cars on the roads, only so many kilometers of roads, and only so much energy to fuel our need for mobility. Growth is unlikely to continue in a similar fashion due to both internal and external reasons that saturate the system.

What follows therefore is an inevitable paradigm shift – either due to the new definitions of mobility (Goodwin, 2013), (Moriarty & Honnery, 2008) , or due to the change in the dynamic of automobility evolution (Farla et al., 2010), (Jeekel, 2015). Considering the Multilevel Perspective on the system innovation (F. Geels, 2006), these changes in the socio-technical landscape affect all of its regimes, and niches that are involved in its definition. Hence, major challenges, risks, as well as opportunities are to be seen in the socio-technical components that make up mobility as it is.

A somewhat overlooked, yet vital aspect to the effective establishment of automobility systems is the creation of sustainable and efficient road infrastructure. Whenever automobility innovation is considered, we tend to discuss the latest developments in alternative propulsion systems, battery technology, ICTs, etc. Rather infrequently we look at the surrounding technologies and emerging innovations that greatly affect the course of action of the major niche. This is especially unfavorable, when considering the road infrastructure. Its developments are crucial to the sustained improvements and innovations seen across the spectrum of the automobility system. EV recharging solution, including on- and off-street charging is needed for the widespread of e-mobility (Kemp et al., 2010). Likewise, enabling vehicle-to-vehicle, and vehicle-to-infrastructure (Bleijenberg, 2012) is essential for further improvements in Co-operative Adaptive Cruise Control (CACC), car platooning (Arefizadeh & Talebpour, 2018), and finally – autonomous driving (Fagnant & Kockelman, 2015). Moreover, it is the advancement in road infrastructure, which can accommodate new modes of transport and use patterns (Cervero, 2014).

When considering road infrastructure specifically, a major obstacle can immediately be recognized. A significant portion of the development and operation costs has to be allocated for the infrastructure maintenance. What is more, action planning and resource allocation is an arduous process that should be well monitored and optimized. With the road network constantly growing and complexifying, the scale of operations needed for effective upkeep and alignment rises. Moreover, the additional pressure resulting from the increasing numbers of vehicles and our reliance on automobility demands further optimization from the maintenance decision processes.

7.2.2. Goals of the case study

The aim of the case study is twofold. First, this study explores the possibility of using the DRL algorithm as a functional method of decision-making in the field of road maintenance from an entrepreneurial perspective. The goal is to understand the factors that can be affecting the possibility of DRL adoption in this distinct situation. To do so, a literature review is performed, which specifies the promises of Deep Reinforcement Learning solutions, the challenges in the field of road maintenance, as well as evaluates the implementation of Artificial Intelligence solutions in the decision-making setting.

What is more, the research attempts to examine these phenomena within the context through the previously defined framework. Therefore, the Value Proposition for AI solutions is used as a method for the search and evaluation of the adoption factors. The case study distills the particular values that can be observed in the scenario of road maintenance and places them on the Value Proposition Canvas. By doing so, it analyzes if the product market fit can be obtained, and if the DRL implementation is applicable in this case. The motivation is also to assess the proposed framework via a real life scenario.

7.3. Case study literature review

7.3.1. Relevance of the road infrastructure on the system of automobility

The applicability and necessity of the innovation in the road infrastructure maintenance has been described in the context and motivation for the exploratory case study. The scientific papers that were studied show the relevance of niche innovation in processes of mutual development of both automobility systems and road infrastructure (F. Geels, 2006), (Urry, 2004). The requirement for innovation within the infrastructure segment has also been shown (Cervero, 2014), (Fagnant & Kockelman, 2015), (Cresswell, 2010). Maintenance of the system itself is a major contributing factor to the lagging of innovation in this particular field, as the costs may be holding back investments for large scale applications of new solutions and technologies.

7.3.2. Promises of DRL on infrastructure assets maintenance

The literature research in this problem area was done in three consecutive, yet somewhat overlapping steps. Firstly, articles generally describing the notions regarding deep reinforcement learning were analyzed. It has been shown that the technology can deal with large data sets, and find optimal problem solution pathways (Richbourg, 2018). What is more, the industrial applicability is at high level. As a matter of fact, a vast portion of the articles deals with the application of DRL algorithms in the industrial setting. It has been stated however that – like any other technology – DRL comes with some drawbacks. There are several prerequisites for the applicability of the algorithm. A large amount of uniform data is needed, as well as a good understanding of the network behaviors (El Bouchefry & de Souza, 2020), (Richbourg, 2018) Predictive models have to be setup in order for the algorithm to define the optimal policy pathway. With at that being said, what sets this approach apart from other technologies is a low cost of implementation of the actual algorithms and the model's ability to self-improve, as more and more analyses are made.

Furthermore, the applicability of this technology was analyzed from the perspective of the decision makers. The policy pathways can indeed be used by the policy makers to optimize maintenance planning and execution (Huang et al., 2020), (Marović et al., 2018). With a more effective planning procedures, in addition to a clearer understating of alternative outcomes, budget waste may be prevented (Darvishvand & Latifi, 2021). The literature also points to significant improvements of other aspects relevant to the decision makers – optimal time allocation, reduction of emissions, more effective system performance (Andriotis & Papakonstantinou, 2018). Still, implementation of such algorithm in a rigid decision setting may be a challenge, as it might have a considerable impact on the operation procedures, definition of responsibility, and execution.

Subsequently, the specific application of the DRL algorithm in the road maintenance setting was studied (Han et al., 2021). Research presented 90% accuracy in the decision making process for pavement inspection and maintenance, as well as a 4.35% higher action accuracy and 75% reduction computation time, compared to the state of the art method (Han et al., 2020). Furthermore, the proposed algorithms allow for definition of long term maintenance planning (up to 20 years) (Darvishvand & Latifi, 2021), which may be further improved based on the user input (Andriotis & Papakonstantinou, 2020). DRL algorithms show promising results in the predicative maintenance scenarios, should the input data be well organized and provided (Marović et al., 2018).

7.3.3. Road infrastructure maintenance challenges

So far, two major contributing factors to the challenges imposed on the road infrastructure that are described in the literature have been found. The first is the increasing reliance on car usage (Goodwin, 2013), (F. W. Geels et al., 2017), resulting from increasing number of cars, population, and dependency on automobility. What results from such dynamics is a constant state of road overuse, which further contributes to the maintenance challenges (Pais, Figueiras, Pereira, & Kaloush, 2018). This creates a situation of unreliability of the previously generated pavement degeneration models. Initial assumptions of road pavement lifespan seem inaccurate with the increasing number of vehicles as well as climate change (Mallick, 2016).

Particularly in the Netherlands, these trends have considerable implications. Although the general state of the road network today is of high level, these dynamics raise questions and concerns among researchers (Erkens et al., 2015). The situation is complexified by the ineffective budget allocation, or even budget cuts (Rietveld, Bruinsma, & Koetse, 2007). As stated by Erkens et al., these rapid changes are felt by the infrastructure system and its stakeholders, and further improvements are required to address the new challenges, which may soon appear. Currently, TNO is responsible for carrying out research and development in the field of road maintenance; specifically an automated ravelling (i.e. surface stone loss) inspection system is setup as an innovative method of evaluation of the road conditions (Aalst, Derksen, Schackmann, Bouman, & Ooijen, 2015).

A trend that can be noticed in the solutions discussed in the literature is the need for adaptive planning tools and decision making systems, which would be able to comprehend the vast and growing complexity of the road networks (Arts, Leendertse, & Tillema, 2021). Moreover, a shift in the decision-making process is seen worldwide, where the national governments divide the responsibility of road maintenance among provinces, and municipalities. The same perspective is applicable in the Netherlands (Rietveld et al., 2007). Rijkswaterstaat is responsible for innovations in the pavement surface monitoring, but it should be noticed that the local governments are unable to use this scanning technology due to its complexity of operation.

The research paper of Han et al. (Han et al., 2021), goes into great detail of significance and applicability of several road maintenance planning methods. It also provides an example of implementation of reinforcement learning algorithms in the field of pavement maintenance. They also list the advantages drawbacks of the commonly found operational, metheuristic, and AI decision making solutions in relation to physical asset maintenance. Specifically for the artificial intelligence, they list the degree of precision as its main strength. Nonetheless, the provision of clear, orderly data and predictive models is a definite requirement, as confirmed in the AiDAPT article on DRL (Andriotis & Papakonstantinou, 2020).

7.3.4. Implementation of Artificial Intelligence in the decision-making setting

This problem area defined possible pitfalls, challenges, and notions that must be considered by the stakeholders during the implementation of the DRL algorithms in the decision-making setting. It has been mentioned previously, how the implementation of the algorithms necessitates the data and model availability. The literature obtained for this problem area deals more with the generalist perspective on the issues resulting from the application of the reinforcement learning. In their article, Harvey & Gowda defined several regulatory issues and challenges that arise during the implementation of artificial intelligence systems. It can be seen that in other fields, where AI has been previously implemented on a certain scale, the risks regarding data security, liability, and internal operations remain unsolved (Harvey & Gowda, 2021).

Zuiderwijk et al. presents a systematic literature review on the challenges and significance of AI use in the field of governance (Zuiderwijk et al., 2021). They highlight the necessity of AI adoption, nonetheless the paper raises the concern that the adoption rates in the governance bodies has been lacking. This literature review goes into great detail on potential benefits and challenges that were seen in the cases of AI adoption by decision-making bodies. Evaluating, confirming, and addressing these issues seems vital during the possible adoption of DRL algorithms.

Similarly, the article by Galaz et al. confirms the propriety of the risks and challenges, and further delineates systemic risks that were seen in the AI adoption in several industrial fields (Galaz et al., 2021). Another article assessing the AI in the era of Big Data highlights (among others) the challenge planning scope definition (Duan et al., 2019). An important issue is the possible lack of trust of the authorities in the innovative solutions (Valle-Cruz et al., 2021), as well as the necessity of reforming the decision-making departments, including training and team readaptations. Finally, the necessity of evaluating and measuring the benefits, compared to traditional decision-making methods is brought up (Sharma et al., 2021).

7.4. Methodology

7.4.1. Case study participants

For a part of data collection, a series of interviews have been conducted. The goal of the interviews was to acquire knowledge from various fields that are relevant to this case study. Therefore, experts in the field of Artificial Intelligence, specifically oriented towards DRL applications in civil engineering were asked for their input on the particular aspects of the technology that should be considered in the Value Proposition. Moreover, a business developer experienced in data collection systems and smart solutions provided valuable insights into adoption of such solutions by decision-makers, as well as helped in the evaluation of the value proposition design. In a similar way, a business developer and a CEO of a high tech spinoff from TU Delft evaluated the adoption framework and the resultant Value Proposition. Finally, a representative of TNO, the Dutch Organization for Applied Scientific Research answered questions about the methodology of road maintenance in the Netherlands, data collection procedures, and the potential obstacles in implementation. Table 7.1 lists the participants interviewed for the exploratory case study.

Table 7.1: List of participants in the exploratory case study

No.	Role	Field of expertise
1	Postdoctoral researcher	Delft University of Technology, Faculty of Civil Engineering, AI application in structural mechanics

Continuation of Table 7.1		
No.	**Role**	**Field of expertise**
2	Assistant Professor	Delft University of Technology ; AI in Structural Design & Mechanics
3	Innovation manager / business developer	R&D / Innovation dept. Data collection systems, smart solutions
4	Business developer, CEO	TU Delft high tech university spin-off, smart solutions
5	Research & Development	TNO; Asphalt and road construction innovation and research

7.4.2. Market factors

The analysis of the obtained information allowed for the definition of the following market factors that are relevant to the notion of DRL implementation as a decision-making system in the road maintenance context.

1. The deterioration of the networks of the physical assets may not be accurately represented by the currently used models due to the unreliability of the previously generated deterioration models. Moreover, the asset network complexity, paired with its significant growth in the last years further reduces the precision and effectiveness of the present-day solutions.

2. Maintenance management decision making bodies are yet to implement AI solutions. There is little linkage of models to rigorous computational decision optimization platforms.

3. Deterioration of the physical asses is a dynamic progress. Therefore, the methodology with which the decision-making units assess and define their maintenance policies should react to the changing behavior and confront the variability of the processes. Time-frame based assessment, i.e., analysis and policy advice done periodically, is not an effective nor optimal method for these kinds of actions.

4. Action planning is a multi-objective, multi-constrained optimization issue. Budget limits, operational constraints, availability and uncertainty, material shortages, and other factors must all be considered by decision-makers. Sustainability and risk measures, as well as

safety expectations dictated by societal needs and political decisions, must be smoothly integrated into the optimization process.

5. Currently available infrastructure management approaches have been permeated by AI-enabled algorithmic frameworks, mostly for predictive models, i.e., constructing data-driven models that can forecast future network conditions. The envisioned application will progress to adopting prescriptive AI models, changing the focus away from prediction-centric infrastructure management tools and toward decision-centric infrastructure management.

Classical decision-support systems lack the ability to integrate real-time, inherently unpredictable information from data and observations. The discussed Artificial Intelligence system was based on partially observable Markov decision processes, which addresses all of the aforementioned concerns. It relies on the provision of deterioration data, either in a form of historical data, or deterioration models.

> *"For the DRL application in maintenance, we need the deterioration data – how the roads degrade over time, how the physical system changes. Usually this can be provided by the stakeholders – the maintenance company, or the client for whom the framework is being created. Additionally, we must define the actions that are possible to be taken, and how these actions interact with the system. What does it mean to make a repair for a certain system or for a certain component. Also – what do these action mean financially. Finally, the current way, in which the system is inspected and maintained."*
>
> *Postdoctoral researcher, Delft University of Technology*

Solutions are needed that can provide appropriate inspection and maintenance policies with the lowest life-cycle cost while eliminating related life-cycle risks and ensuring the systems' long-term operability. Traditional procedures, such as age- or condition-based maintenance strategies, risk-based or periodic inspection plans, and genetic algorithm-based optimization approaches, are notoriously difficult to handle when dealing with multi-faceted situations. Many of these methods have issues with optimality, scalability, uncertainty-induced complexity, and the inability to account for restrictions.

When implemented in real life, the system has the potential to save a significant portion of the budget, and possible users range from the governmental agencies to private businesses.

A significant part of the infrastructure assets approaches, or has well exceeded its designated structural life. The implementation might become more important in the near future as the consequences of climate change and related uncertainties, which are difficult to estimate, make finding lifelong optimal control and adaptation plans for infrastructure systems ever more complex.

> *"Costs are not only direct, but also in a form of social costs, sustainability, etc. If you look at reasons for this situation, you realize that it is hard to estimate them and include them. Policy makers are struggling with how to put a framework, where you can compare these costs – especially these outside the company. Because you know the costs within your company, but what about the costs that society pays?"*
>
> *Business developer, TU Delft High-Tech Spinoff*

7.4.3. Technological factors

The realized decision-making system would be able to react to the actions defined by the decision-makers, updating the asset status, and adjusting the policy pathways. In its core, it combines the model-based engineering with the data-driven approach. In this way, the action planning can be effectively scheduled for longer periods of time. Moreover, the system can handle large data quantities resulting from the modelling and condition assessment of the network. The implementation of uncertainty, safety, sustainability, and other constraints is well possible. The system should be viewed a dynamic 'policy map' instead of a static list of required actions. User would be able to interact, test solutions, redefine constraints, and decision rules. Such approach can reduce maintenance costs in the order of 30% compared to conventional asset monitoring and maintenance methods.

> *"We have someone, who sees the numbers and performs actions. However human beings lack the capacity to make such complex decisions and it is very hard for us to find correlation in data arrays of millions of entries. The AI algorithm has this capacity – so it can also work on top of other applications, however it also depends on their nature. In my experience, you have a data collection system, and above that system you just have to replace the module responsible for the data analysis, and it is replaced by the AI solution."*
>
> *Innovation Manager, R&D / Innovation dept. Data collection systems*

The user could benefit from the product in three ways. Primarily, it is possible achieve significant cost savings compared to the currently implemented methods of decision making. Additionally, the ability to plan for an extended period with a clear understanding of the alternatives of other options seem promising. Finally, resource efficient maintenance due to action combinations is possible due to the analysis of actions beyond feasible scopes of classic policy modelling approaches.

The optimized policy pathway should be regarded as a dynamic decision set, which is able to react to the user input. As new information comes from data on the condition of the system, the policy and its cost are updated. Therefore, the policy report and hence the long-term maintenance planning can be kept up to date with the external events. The algorithm seamlessly handles new data and provides an optimal solution for the new data set. Additionally, by optimizing the operation scheduling, some maintenance actions can be combined. To give an example – it might be possible to perform maintenance on neighboring segments of the network, as the total cost of action would be lower, even if the life expectancy of the other segments would not indicate the necessity of action. This is achieved with the DRL's ability to perform policy optimization on the entire network with the consideration of all possible costs and actions.

> *"In the decision making domain, it is not only able to recognize patterns, but is also able to come up with sophisticated sequences of actions to reach its goal. So it can develop a strategy. Hence in this case, the AI can help us scale very high dimensional systems. It can recognize patters in large data sets, but it can also work in high dimensional spaces that do contain synthetic data (they come from simulators) – AI can interact with the simulators and make excellent, efficient decisions in these domains."*
>
> *Assistant Professor, Delft University of Technology*

7.5. Case study results

7.5.1. SWOT analysis of the DRL application

The information obtained from the literature and the expert interviews can be used to create an overview of the most significant benefits and issues observed in the proposed DRL decision-making system. The previously defined framework for AI adoption guides the thought process and provides general insights into the studied matter, and therefore allows for a clear definition of the problem and opportunity areas. By knowing what are the general trends and notions behind AI adoption, the distillation of individual factors is made easier. SWOT representation creates an overview of the most critical aspects of the solution that have to be taken into consideration during the solution development and implementation processes. Moreover, it allows the developers a method of communication with the potential clients and stakeholders and obtaining relevant information that may be useful during said processes. Figure 7.1 presents the SWOT analysis for the DRL application in the road maintenance setting.

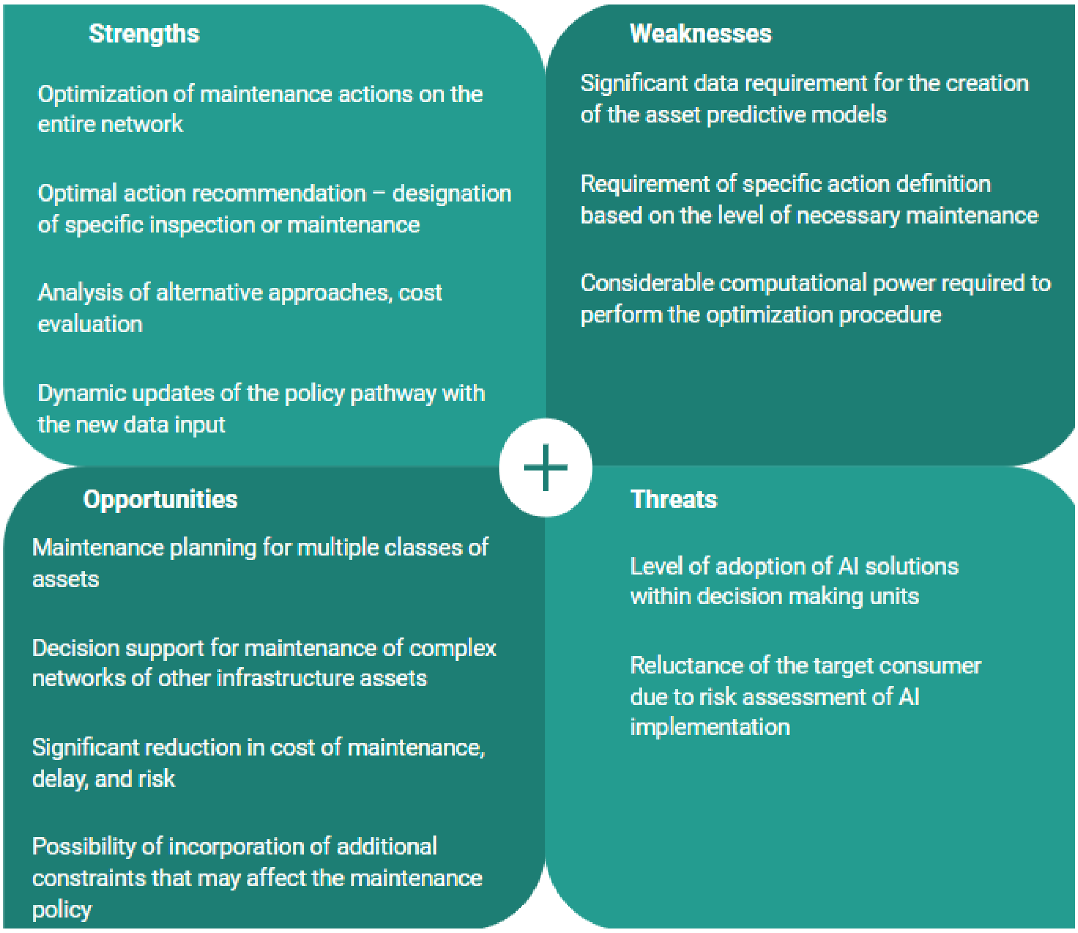

Figure 7.1: Strengths, Weaknesses, Opportunities, and Threats (SWOT) analysis for the DRL application for decision making in road maintenance

7.5.2. AI VPC - impact of adoption factors

In this exploratory case study, the previously defined AI solution adoption questions were used in the Value Proposition Creation method. The goal was to test their relevance and impact on the value design. Initially, the regular VPC methodology was used (Osterwalder, 2014). Primarily, it assumed defining the gains and benefits of the proposed solution, as well as the potential customer pains and needs using a set of guiding questions (Appendix C, D). The VPC is a creative, repetitive process. The canvas is meant to be built in a Lean way, quickly and efficiently, and then tested with relevant actors. Therefore, initially a simple Canvas was built, based on the assumptions and ideas found in the literature.

The supporting adoption questions have been used after the first Canvas iteration. By asking the questions, the values were redefined to better fit with the realistic assumptions and potential implementation hazards. An observation was made - the value Canvas required at least one iteration and verification of its assumptions with the relevant interviewee. The adoption questions are more specific, and require external knowledge on the actual application. In order to answer them, the solution developer must have a testable idea predefined, as otherwise answering them provides no verifiable results. The general knowledge obtained during the course of the case study literature study allows the questions to be answered more specifically too. It can be safely assumed that due to the intrinsic complexity of AI technology, a certain level of expertise is required in the technological domain.

By using the adoption questions, the values presented on the model became more specific and relevant to the application. Moreover, by using the questions, the total number of presented gains and benefits has significantly decreased (from initial 83 to 45). The decrease in the number of values presentable on the Canvas is to be expected during normal VPC method - the iterative nature of the framework makes certain values redundant in the process of verification. Nonetheless, the decrease was significant. It is difficult to estimate, how many values were rejected / combined on the basis of the adoption impact. Both sets of questions are meant to be guiding the process, and not provide very specific results. This decline could have been also affected by the specificity of application and the complexity of the AI technology.

The adoption factors helped in creating a value set that is more specific to the particular use cases of Deep Reinforcement Learning in the context of road maintenance planning. To provide a few examples, the following changes can be attributed to the guidance provided by the solution adoption questions. A distinction on the data input has been made – the proposed solution must predict the necessary maintenance actions based on the pre-defined predictive deterioration models. Additionally, historic data has to be included as a source. There is a strong need to assess alternative actions, not only the most optimal schedules. This requirement takes into consideration the external factors that can interrupt or obstruct the maintenance actions. Additionally, unnecessary actions have to be avoided. Moreover, not only a schedule and a cost definition is required. The solution should also be able to dynamically allocate the necessary resources in order to comply with the current operation methods. The increased asset lifespan is one of the key values of the proposed AI tool; it can be set on par with the reduction of the needed maintenance budget.

From the perspective of the potential customer, the adoption questions helped to define the pains more concretely. It turned out that the initial assumption of simultaneous maintenance of multiple assets from the very beginning of the solution introduction was too bold. The value of combined asset maintenance is relevant, however the biggest pain can be seen in the untimely maintenance, rapid changes of schedules, and the inability to see well into the future. Moreover, there seems to be a certain hesitation towards the introduction of the AI due to the significant impact it will have on the operations. Therefore, the number of features has to be kept at minimum, and the solution must specialize in the particular actions assigned. It was also discovered that potential scaling of the application for other markets – in this case: municipal and provincial roads can be challenging due to the differences in data input, length of the planning periods, as well as dissimilar approaches to the maintenance and inspection actions (varying levels of deterioration corresponding to different asset states).

7.5.3. VPC for DRL decision-making application

The findings of the case study can be presented on the Value Proposition Canvas. Again, by using the previously defined framework for AI adoption and AI value proposition, distinguishing the individual benefits and factors for the specific application was possible. The understanding of the aspects that affect the adoption of the AI solutions, as well as the ways in which these aspects interact with the VPC made the definition of product features more straightforward and comprehensive. Figure 7.2presents an example set of values of a Deep Reinforcement Learning system used in the context of decision-making for road maintenance.

From the perspective of a potential customer, their goal is to obtain time savings from the optimized scheduling of the maintenance and inspection actions that considers all the possible scenarios of carrying out the actions. Additionally, money savings could be realized from the optimal resource, manpower allocation, clearly defined planning, increased asset uptime, reduced cost of repairs - fixing something ”small” before it turns into an expensive failure. The saved effort could come from efficient maintenance actions: possibility of carrying out combined maintenance actions. The customer wants a better overview, a plan of the maintenance and inspection actions. Their wish is to know “what happens when, where, and how”. What is

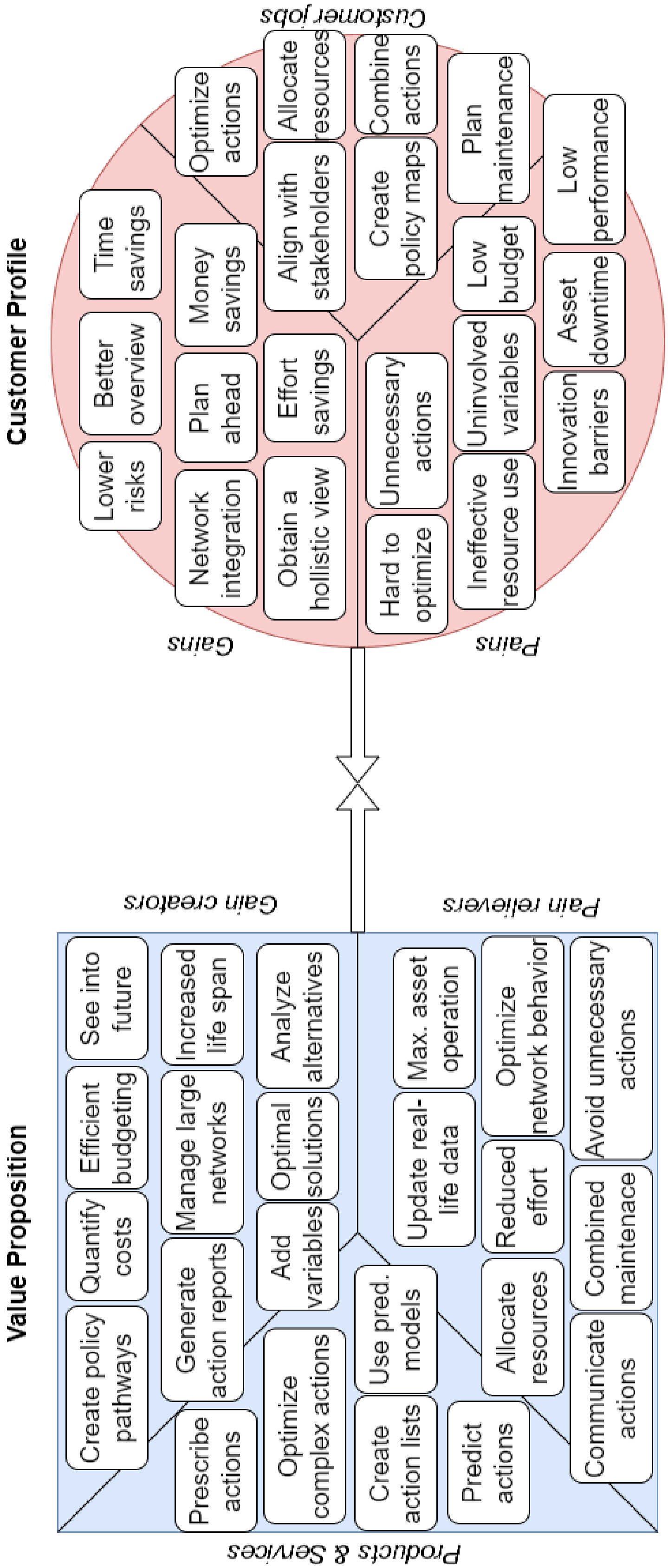

Figure 7.2: Example Value Proposition Canvas defined for the DRL implementation for road maintenance

more, they wants less optimization of the decision making process of the maintenance planning. The customer wants to spend less time looking into scenarios. The customer has a set budget within which the maintenance has to be carried out. Within the budget, the customer expects a feasible and tangible plan that they can directly provide to the crews / departments / engineers, who carry out the actual maintenance actions.

From the operational perspective, the customers look for a method for decision making in very complex and uncertain systems. They want to optimize something that is far from trivial, that has so many possibilities that it is impossible to calculate every single one. The customer looks for a way to integrate the entire network that must be maintained. They want a holistic view that indicates the details about every single segment. The ultimate method would say how to fix the problem, not just tell you that there is a problem with an asset. Additionally, they want to update their decision making method with new information and data, and use it to improve their processes. Planning is successful, when the maintenance fits the allocated budget, risks are mitigated, there are no failures, the network of assets is operational for the longest possible time. The cost can be gauged by: inspection and maintenance actions, delays, risks.

The main difficulty is potentially not being able to see the most optimal way of planning maintenance actions, because the decision making environment is too complex. It may become necessary to for example resend the maintenance team to a location, which is very close to the one, where maintenance was previously done. Maintenance causes delays, closing down of the infrastructure. Moreover, there is a threat of cutting down the on maintenance due to inability to fit within a budget. Another difficulty is the maintenance project delays due to a higher priority action; not seeing the possibilities initially may interfere with optimal planning. Closing down the assets for too long for maintenance means that there is an ineffective use of resources. This situation also happens, when not considering additional variables that affect the maintenance schedules. This inability to see trends in the maintenance actions translates into the inability to catch uncommon failure modes.

The realized solution must therefore have the ability to see into the future, and plan ahead accordingly. Moreover, it should be able to asses several policy pathways based on their individual costs. It has to be aware of the asset conditions and the budget and other restrictions. Based on this awareness, it defines what has to be done to every single asset, therefore optimizing the schedule to be most (cost) effective, without allowing for any failures of the assets. It should be noticed that the customer may not be aware that doing combined maintenance, even if the additional asset is still well performing, may be more optimal / cheaper.

The savings of the realized solution would come in different forms. The client would save time looking for feasible schedules, creating action schedule reports, defining the maintenance goals. Additionally, resources are saved by optimizing resource allocation, combining / doing maintenance actions effectively and having the assets maximize operation time by understanding and assessing the alternatives. Finally, effort could be reduced by knowing what happens when, where, and how; by being ahead of the time in terms of scheduling. In this way, maintenance is done only when necessary.

The strength of the DRL algorithm is also realized by optimizing multiple variables at once. An expert can do one aspect at a time. Here, additional constraints and factors are involved, such as safety, risk, sustainability. The algorithm decision-making method is able to manage large complex structures / networks, optimally address their maintenance and inspection requirements. The proposed product would be able to find solutions to complex decision making problems that are multivariate in nature and consider a vast number of possibilities.

7.6. Discussion

Harvesting the potential of DRL implementation seems to be a challenge not only from the technical perspective – but also (if not primarily) from the side of implementation within the decision-making body. Despite very specific conclusions and approach recommendations, current literature lacks evidence-based methodology for a step-by-step implementation of AI in the maintenance planning. This was to be expected, considering the fact that our knowledge and expertise in the field of artificial intelligence is young and lacking. It can be however concluded that the transition pathway for the DRL must be made based on evaluations of literature, case studies, and analysis of opportunities and challenges seen in other AI applications.

The knowledge gap presented in this study can be seen in the absence of sufficient understanding of the implementation processes. From the theoretical perspective it has been established that the implementation of Deep Reinforcement Learning algorithms is possible in the road maintenance planning scenario and that it may in fact be favorable compared to other decision-making techniques. The necessity of innovation in the road infrastructure is also acknowledged in the literature. What is unclear however is how – given the availability of the data and predictive models – should the algorithm application be implemented, and what are the challenges and obstacles along the way. Many sources point towards problem areas, which can be detailed in the analysis process. What is more, they offer some solutions from other applications and AI implementations. Still, expertise is lacking when it comes to practical solutions and challenge definitions in the AI decision making setting.

Considering the matters enclosed in the introduction, the relevance of infrastructure maintenance on the overall performance of the system of automobility is undeniable. What is yet to be understood is the innovation potential that can be unlocked with more cost and time effective upkeep planning. The challenges that lie ahead the future road networks are significant. The adaptability to the growing number of vehicles, and adoptability of automotive innovations (EV charging, platooning, autonomous mobility) are becoming increasingly vital to the automobility system performance. It can be argued that without solid, cheap, and effective maintenance of the roads, the possibilities of innovation diffusion are limited. Whatever the scope of the upcoming developments may be, it is undeniable that mobility, and therefore many areas of our lives rely on efficient and dependable infrastructure.

8 Discussion

8.1. Answering the research questions

The main research question of the thesis was stated as: *"What are the factors influencing the specific value proposition of innovative AI solutions."*. These factors were attributed to the adoption of the Artificial Intelligence solutions by the customers, and can be defined as: Data availability, Integration with current methods of operation, Experience of the stakeholders, Internal capacity for implementation, Previous experience, Perceived costs of implementation, Perceived benefits of implementation, Differentiation from other solutions, Organizational agility, Organizational structure, Technology and innovation awareness, Leadership support, Trust in AI solutions, Bias in AI, Moral, ethical, and social concerns. The adoption of the AI solutions has been analyzed from the perspective of its impact on the AI value proposition, defined using the Value Proposition Creation. The adoption factors, together with their relevant examples were grouped and assigned to the particular fields of the VPC, based on their potential impact. Exploratory guiding questions were defined in line with the VPC methodology, based on the impact factors and provided to be used during the value definition in the VPC.

By studying the relevant literature sources, several contextual factors were found that can be involved in the process of Artificial Intelligence solution adoption. The reason, why the adoption processes were studied is to find the relevant factors, which impact the AI solution throughout the implementation process. By understanding these factors, business developers may be able to craft the value proposition design in such a way that it involved the answers to the problematic areas and emphasizes the strengths of the solution. Moreover, knowing the obstacles ahead of the implementation process may allow to steer the development process around them.

A conceptual model was formed, which showed the relationship of the groups of factors on the AI adoption process. This model was then used during the empirical analysis part, where AI experts from various fields of research and development were asked to evaluate and provide insights into these factors. Various codes were obtained, which allowed the designation of specific aspects to the general adoption factors. Furthermore, the relationship between the factors was analyzed. It is important to remember that the adoption factors do not act in a vacuum, and that they often interact with each other. Knowing these relationships allows for an evaluation of the Value Proposition design, as well as mitigation of design and implementation issues before they impact the solution adoption. Afterwards, the Value Proposition Canvas was used to locate these factors on the product Value Map and potential Customer Profile. In this way, the impact the adoption factors may have on the AI product's Value Proposition was provided.

The factors can be divided into aspects that influence the product and potential customer profile. The reason for this differentiation is the added clarity of analysis. Not all of the adoption factors may influence, how the solution behaves, or what the attitude of the potential customer may, or should be. Therefore, on the side of the product value proposition, the perceived benefits and costs of implementation affect what the solution can achieve, and what troubles one can expect, when adopting it. These go beyond the strictly technical aspects, and may involve the notions of operational improvement, adaptability, as well as impacts on other solutions that the customer may be utilizing. Moreover, because the AI solution has to be carefully adapted to the customer requirements, the previous experiences of the potential client, together with the 3rd party stakeholders involved in the adoption process have to be taken into consideration. Although the AI solutions may be realized as low-impact, and not requiring advanced computational facilities, a analysis of the internal capacity for implementation should be performed. Still, the most important significant factor that affects the AI product's value proposition is the data availability. It has been throughout the research that the amount, quality, and transferability of the data can be the one most significant factor that affects the solution's value proposition, AI system performance, adaptability, and overall effectiveness. Therefore, it can be said with a great deal of confidence that the primary aspect, which the solution developers have to consider, is what kind, amount, and quality of data can be obtained in order to craft a solution that is feasible, implementable, and which's benefits are realizable by the customer.

As it turned out, the customer's perspective on the system abilities is often ambiguous, unclear, and potentially wrong. Clients may either want the system to perform too well, and achieve impossible computational efficiency, or on the other hand may not be aware of the potential, ease of use, and applicability. Similarly, their perspective of necessary costs may follow a similar train of thought. Therefore, the value communication and clarification of these aspects is so necessary on behalf of the developer. These factors may also fall under the category of technology and innovation awareness, which shows the consciousness and apprehension of the solution capabilities. These factors are also reflected in the trust and bias aspects. It has been shown that the lack of understanding of the operational methods, potential risks, and overall system performance may induce distrust and question the solution overall integrity. Additionally, AI raises certain moral, ethical, and social concerns, which affect the readiness, willingness, and ability to adopt the AI solution. Yet again, these factors must be reflected in the AI value proposition, as without a thorough explanation of the system capabilities, the users may not be able to trust it as a whole. On the side of the organization adopting the proposed AI solution, the structure and agility play a significant role. Certain methods of the organization operation may need to be altered, the value capture process for AI solutions differs from conventional strategies, and some previously adopted methods may become redundant. What is more, the leadership support is important to effectively communicate, manage, and oversee these transitions.

Guiding the main research question, the thesis stated four additional sub-questions that allowed an in-depth inquiry into the more specific aspects needed for the assessment of the AI unique value proposition design and strategy:

1. **What aspects of the Artificial Intelligence technology are responsible for its adoption?**

These factors are, in no specific order: Data availability, Integration with current methods of operation, Experience of the stakeholders, Internal capacity for implementation, Previous experience, Perceived costs of implementation, Perceived benefits of implementation, Differentiation from other solutions, Organizational agility, Organizational structure, Technology and innovation awareness, Leadership support, Trust in AI solutions, Bias in AI, Moral, ethical, and social concerns.

This subquestion can be treated as a preamble to the main research question. Literature study and semi-structured expert interviews were performed to define the factors. This resulted in the definition of a conceptual model for the Artificial Intelligence adoption. The aspects were divided into several subgroups: Product & Implementation, Organization, Expertise, Market, and Miscellaneous factors. Among these groups, the specific factors responsible for AI adoption were listed. Moreover, the interviews provided a long list of codes, which were categorized and connected with the specific subgroups. In this way, an overview of particular aspects related to the AI adoption was created (seen in figure 5.1). Obtaining such overview was helpful in defining the individual benefits, pain relievers, and gains of the product, necessary for the AI Value Proposition. By understanding the aspects that fall into the AI adoption categories, the developer is able to navigate the solution creation process and include all of the needed features and communicate them via the value proposition design.

2. **How to assess the benefits and opportunities of an AI solution in face of the technical abilities of the Artificial Intelligence technology?**

The study showed that the Value Proposition Canvas can be a useful tool, especially if the solution adoption factors are taken into consideration in a form of the guiding questions, used in parallel to the Value Proposition process. By assessing actual, feasible solutions, the product developers are able to guide the VP process and make realizable claims on the proposed benefits and opportunities. Grounded in reality by the imposed adoption factors, the achieved Value Proposition can explore the potential innovative applications without compromising integrity or making bold statements.

Because of the overall complexity of Artificial Intelligence solutions, the assessment of benefits and opportunities is not trivial. The AI adoption model allowed to categorize the specific aspects of the AI solutions that must be considered during the implementation process. Through the careful analysis of the factors, and consultation with the AI research and development experts, the connection with the Value Proposition Creation framework was made possible. The framework assumes the allocation of certain product features and values on the provided canvas, and then searching for a product-solution fit. The factors that were found to be correlated with the adoption of AI solutions were then placed on the VPC, however not as values, but rather guidelines for effective definition of said values. What aided this process is the establishment of the connections between the adoption factors, their relationships and dependencies (figure 5.2). In this way, the convoluted nature of Artificial Intelligence was somewhat untangled, and allowed for the assessment of benefits and opportunities.

3. **How to create a meaningful connection between the user need and technical ability of the AI system?**

Value Proposition Canvas is a simple, yet effective model that connects the user pains with the proposed solution benefits. It may however be too elementary, when complex solutions – such as AI systems – are analyzed. Therefore, it becomes crucial to ensure the feasibility of the value proposition by considering the product adoption. The proposed adoption questions were based on the crucial, commonly stated aspects of the AI adoption factors, in turn allowing to assess the problem complexity, technology absorption capacity on the side of the user, and potential pitfalls and design challenges on the side of the solution developer.

The factors that are responsible for successful AI adoption were placed on the VPC, and then during the case study, an example application – specifically the DRL in the decision-making context for road maintenance planning – was analyzed. Particular values, benefits, features, and solutions were listed on the VPC by using the previously developed frameworks and methodologies for the AI applications. Because the factors involved in adoption were known, it was more straightforward to list the particular product aspects that are necessary for the product-user fit. During the case study, additional issues were also uncovered, namely the data availability and ability to implement AI solutions in governing bodies, which directly correlated with the previously found aspects. In the end, the fit was obtained by comparing and contrasting the resultant Value Proposition Canvas and the individual benefits that were listed.

4. **What are the specific aspects of Artificial Intelligence value proposition that make it unique and challenging to design?**

Artificial Intelligence solutions are based on a complex, not well understood technology that promises radical changes to the computational and operational methods. The implementation requirements are often unclear, the promised efficiency and benefits may seem exaggerated, as well as there are many misconceptions and concerns surrounding the AI. Additionally, implementation of AI solutions may thoroughly affect the operation methods of the potential user, altering the activities and imposing new requirements. Therefore the value proposition design can be challenging, and its communication with the potential customers difficult.

In order to answer this question, first the value proposition methodologies were analyzed in the literature research. Commonalities and differences between several VP approaches were found. On this basis, the Value Proposition Creation method was analyzed; its strengths and weaknesses were described. In doing so, the potential benefits and obstacles were listed with the consideration of the unique aspects of the Artificial Intelligence solutions. This also allowed for listing good practices for value proposition using the VPC method for AI products, which could be verified during the case study. In general, the AI's complexity makes the customer definition challenging because of the interrelationship of user requirements, data availability, and technical abilities. These complex relations make the value proposition, communication, and capture difficult, as the developer may have a hard time defining the necessary features, and user specifying what they truly expect in the solution. Nonetheless, by using the VPC framework and the overlay of adoption aspects, a certain clarification can be obtained, which further allows to ask the proper questions and resolve the abovementioned issues.

8.2. Research implications

8.2.1. Theoretical implications

The research contributes to the theoretical understanding of the methods used in the value proposition, specifically to the Value Proposition Creation (Osterwalder, 2014). Despite its usefulness and proven record, VPC lacks solid theoretical background and academic insights. This in turn makes the VP results verification questionable. The paper aims to enlarge the body of knowledge, provide sufficient references, and evaluate the VPC through the lens of other Value Proposition models (Payne et al., 2020). The method used in this paper demonstrated the potential improvement of the VPC approach with a evidence-based practices of integration of the AI adoption factors. Contrary to some approaches (Belleflamme & Neysen, 2020), (Carter & Carter, 2020), the goal was not a modification of the Canvas itself, as the general method is tried and tested; its main strength lies in the model's simplicity and ease of use.

With a better understanding of the VP methods for complex AI solutions, together with the incorporation of adoption factors as a reliable measure and guideline for value definition, the research hopes to improve the AI value proposition methodology, increasing the chances of successful AI implementations beyond the proof of concept stages (Sjödin, Parida, Kohtamäki, & Wincent, 2020). Additionally, a refined value proposition addresses the issue of the conceptualization of the AI technology (Linde et al., 2021), (Margaret Taylor, 2012). It aims to ground our goals and hopes in reality. The theoretical considerations on the nature and abilities of the Artificial Intelligence solutions become more sensible, pragmatic. With the transformative potential of the AI (Borges et al., 2021), the theoretical understanding of the solution relevance, adoptability, and impact on the operation methods is highly required.

There is a significant need for evidence-based business frameworks that employ verifiable and traceable research methods. The research included a significant literature study, which served as a background for evaluation and further model development. Additionally, it aims to collect multiple sources of information and present a valid research methodology for the Value Proposition practices. The paper provides a structure, which proves that the VP models can be evaluated, analyzed, and augmented with the consideration of the scientific methods. It leaves an open door for the future research on the impact of other aspects of the Artificial Intelligence on the value proposition methods, verification and testing of said frameworks, as well as the relevance of this approach for other high tech solutions.

The developed conceptual model for the AI adoption confirmed the findings of multiple other researches that looked into the factors involved in the implementation processes. Via the literature search, expert interviews, and the case study, the necessity of data availability has been highlighted. This finding has been the reoccurring theme and oftentimes it seemed that the lack of data is the main issue blocking a successful implementation and use of the AI. Additionally, many of the studied adoption models mentioned the necessity of the AI integration with other methods of operation. This is because these solutions rarely act alone; more often AI products are a part of a decision-making, result optimization, or computational systems. While discussing these notions with the AI experts, the integrability of AI has been mentioned as a major advantage of these products, but also a certain obstacle in adoption. The methods of operation of a potential customer organization have to be made clear beforehand. What is more, an often mentioned factor, both in literature and by the experts, is the notion of trust and understanding of the AI solutions. Because of the intrinsic complexity of the AI solutions, lack of the necessary comprehension often turns into distrust and unwillingness to implement them.

Additionally, the thesis added to the already existing body of knowledge on the Artificial Intelligence systems. By understanding and combining the adoption factors into the AI adoption model, and correlating these factors with the Value Proposition Creation framework, a better comprehension of the AI value proposition has been achieved. This process fills a certain knowledge gap, as currently not many papers provide an in-depth look into how the AI values are distilled and defined. Although Artificial Intelligence as a technological domain is not a necessarily new concept, the ideas on how AI behaves in the organizational, or business settings are still clarifying. It is a challenge to provide a comprehensive value proposition of an AI product, if there is very little knowledge on the impacts it has on the operational methods, trust building, and organizational structure. This thesis adds the necessary clarification of these impacts from the perspective of value proposition development by a university spinoff. In the cases of MVP development on such a scale, the speed at which a working product can be developed is the primary challenge, and therefore having additional insights into how AI behaves is useful.

8.2.2. Practical implications

What is more, the thesis has certain practical implications, especially from the perspective of a university spinoff, or an AI startup. This is because these organizations are the most likely to be using the relatively simple, generalist methods for value proposition, such as the VPC. Therefore, the methodical approach presented in this report may be of practical value to startups and spinoffs. As the different VP methodologies were compared and contrasted, and then used to evaluate the VPC, a certain number of strengths and weaknesses were defined, which could be well used to guide the value proposition design process in such environments. By stating the recommended practices, not only the value definition process for Artificial Intelligence applications is defined, it also goes beyond by describing the entire cycle for the VP design using the VPC. The notions of value quantification, communication, documentation, and verification are explored and described from the angle of AI solution development. What is more, the example value definition presented during the exploratory case study can be used as a guiding template for definition of particular values of a solution, or verification of the previously made value proposition.

The relevance of this research from the perspective of business development can be seen in multiple ways. First, it proved that the VPC method can be effectively used for the value proposition of complex technologies, such as the AI solutions. The VPC was not internally modified, only certain additions were provided as a specific guideline. Therefore, the potential for the use of this method by business developers may additionally increase. What is more, the research attempted to relate the solution adoption frameworks to the value proposition processes. In general, adoption models are used during the value creation stage of the product development, as a certain checklist and verification method. In this case however, the potential impact of the AI complexity on the value proposition stage is significant, therefore it could be worthwhile to look ahead and consider the later stages of the solution creation. The research provides a way of relating the adoption factors to the Value Proposition Canvas, encouraging the solution developer to consider the future challenges and adapt the value framework, so it can be effectively realized in the future.

From the managerial perspective, the proposed method of incorporating the adoption factors in the value proposition process allows for a more precise and relevant product value and benefit description. The realized solution has a higher chances to fit within the market and respond to the potential customer needs. Moreover, by anticipating future challenges and obstacles, the solution developers are able to adjust and guide the product from the early stages. Especially for the AI technologies, among other high tech solutions, the ability to envision the potential adoption issues and respond to them from the very beginning seems to be highly attractive. Moreover, the proposed adoption questions do not interfere with the general VPC method, leaving it agile and simple. The proposed questions can be also used as a way of generating more realistic value propositions; defining product values that afterwards cannot be realized and adopted is clearly counterproductive.

8.3. Limitations

The main limitations of this thesis research can be seen primarily in the applicability of the defined frameworks to a more complex context. The Value Proposition Creation framework, which has been the main methodology used as a research background and a method development tool, is rather simple (which could be a strength), and hence may be subject to omission of certain aspects. Additionally, the framework assumes that the adoption factors of the AI solutions may be directly linked to the value proposition frameworks. Even though this seems to be the case with the VPC framework – as the methodology allowed for an effective definition of the possible strengths, benefits, and features – the same may not hold true with the use of other VP frameworks. These frameworks may uncover additional relationships between the factors, and place the accent on other aspects, such as customer discovery, market competition, product life-cycle definition, and effectiveness of the solution implementation.

Additionally, as the VPC framework is mostly used by small organizations – such as university spinoffs and startups – this method of value proposition design may not be effective in larger, more complex settings. In these cases, precision and effectiveness take the priority over speed of development and generalization. And although the framework may aid in the process of value definition, it may not be able to comprehend all the intricacies, and interrelationships of factors, which are crucial for VP design in these complex settings. What startups and spinoffs need – which is efficiency of MVP definition – greatly differs from the needs of large corporation, and R&D departments. Still, an argument can be made for the use of these frameworks in the corporate setting in order to quickly define the problem areas, understand the relationships between factors, and aid in the description of necessary research activities.

A limitation of linking the adoption factors directly with the VPC is the potential omission of other relevant factors that could be more significant to the value proposition process, especially in the beginning. One of the goals of the Value Proposition, and especially the VPC methodology is a definition of a feasible value set – not a perfect one – and then testing it in real life. By focusing too much on all of the value dependencies, solution developers can be left stuck in a loop of constant VP readjustment, instead of building 'something' and 'testing it'. The proposed framework addition responds to this limitation by asking the questions in a way that strictly follows the method seen in the VPC. Moreover, there could be other, more significant factors influencing the AI value proposition, other than the solution adoption itself. The research focuses strictly on the adoption, without the consideration of aspects of marketing, product life-cycle evolution, market trends, technology evolution, among others. These, and other factors may in some way influence the VP, hence more research is needed to assess their relevance.

The lack of in-depth academic descriptions, papers, and evaluations on the Value Proposition processes, and specifically the Value Proposition Canvas may be a considerable limitation. Although an extensive literature review has been conducted, the body of knowledge is still relatively young. The VP practices are not grounded in pragmatic, scientific methods. Instead, these are business and management practices that came into fruition by trail and error. Their descriptions often lack relevant reasoning and theoretical grounding. Additionally, the transparency of some of the researches may be hindered; oftentimes best practices are kept in the companies 'behind closed doors'. There is still a big need for a methodical, evidence-based development of business practices, especially when it comes to technical solution development. Nonetheless, the research has been done in accordance to the scientific research methods, and it hopes to add a small block to the scientific understanding of the value proposition processes.

Lastly, it should be noticed that the verification of the AI adoption framework has been done together with the AI research and development experts, whose field of expertise is directly linked with the Artificial Intelligence. It could be the case that from the perspective of nonexperts, certain factors may play a larger role (such as trust, bias, moral and ethical concerns), and additional adoption aspects may be uncovered. It might be worthwhile to look at the AI adoption from a different perspective (i.e. managerial, operational) to uncover additional relationships. Nonetheless, the framework proved effective in the value proposition design during the case study. It seems that the necessary level of complexity of the findings in the field of AI adoption was sufficient for the evaluation of the impact that AI adoption has on the value proposition design.

8.4. Generalization

The goal of this thesis was to define a value proposition model for the Artificial Intelligence that could be applicable in vast number of AI domains. The resultant models include factors seen in varying, different domains. Primarily, in every AI field that has been studies, the issues of data and model provision, integration with operation methods, and trust are uniformly present. However, it should be mentioned that the weight of these particular factors have not been studies. What this means is that in some domains, the importance of specific factors could be different. Nonetheless, such factor representation allows the researcher or business developer to quickly obtain an overview of the most significant notions and therefore inspect individual fields of interested, depending on the actual application.

The VPC is a rather simple, repeatable approach. Hence, the factors used to describe the notions of AI adoption viewed from the perspective of the VPC are very general, and include as many individual notions as possible. This is a conscious and intentional approach. Business developers that use these tools need – aside from domain specificity – a holistic, broad overview that includes multiple ideas, which then can be used for the product development. Additionally, because of the Value Proposition Canvas simplicity, the methodology of the value proposition in the context of AI applications can be adjusted. The entire VPC framework is made to be as general and flexible as possible, in order to comply with the Lean methodology of business development. Because of the goal of the value proposition in the form of VPC – the Minimum Viable Product – the VP framework has to be as generalist, and as crude as possible. The aim is to get the developers to the stage of product viability as rapidly as possible, and allow for testing and implementation in a real life setting.

Finally, it should be mentioned that the approach of analysis of the adoption patters can be successfully used in other high tech fields. The main challenge that has been seen throughout this study is the issue of technology complexity, dependency on external factors, and lack of overall understanding of the solution and its abilities. These issues can be seen in technology fields other than Artificial Intelligence. This has been confirmed, during the exploratory case study. The business developer and innovation manager have pointed out that these notions could be correlated with the application of other solutions. Hence the realized framework – or rather this method of thinking about the individual benefits of a solution based on its adoption – can be extrapolated and modified in order to be used in varying technological domains, where the product / solution complexity is an obstacle.

9

Conclusions

9.1. Future research recommendations

Throughout the thesis, many of the researched aspects generated multiple questions, which could not be sufficiently answered. Regarding the impact the Artificial Intelligence as a technology has on the value proposition design has been only analyzed from the perspective of the Value Proposition Creation framework. By far, it is not the only, not the best VP framework available (however – most often used by startups and spinoffs), and therefore in the context of larger organizations and research facilities it would be interesting to see the AI impact on other VP frameworks. Some of these methodologies were listed, when comparing and contrasting the VPC. Looking at the impact that AI adoption has from other perspectives could be worthwhile, especially because other frameworks emphasize different values, different benefit structures, and different methods for obtaining these values.

Another interesting discovery was made, while interviewing a business developer during the exploratory case study. He mentioned the fact that oftentimes externalized costs (i.e. product / implementation costs paid by others) are not specified in the value proposition. Therefore, when proposing a solution, some of the costs (and possibly benefits) are not directly connected with the user / customer. This impact of the externalized costs and benefits in relation to Artificial Intelligence solutions is unknown. Moreover, one of the more interesting adoption factors that was discussed in great detail by the AI experts was the notion of trust in AI applications. The general consensus stated that in order to built the trust, one should clarify the inner workings of the AI system, its methods of operation, and communicate the impact it might have. However, this might not necessary work for all of the stakeholders, in all cases. Therefore, understanding how the trust towards these new computational and decision-making methods is built, is crucial from the technological and business perspectives.

Finally, the concept for the Deep Reinforcement Learning algorithm as a decision-making tool in the context of road maintenance could be considered as a thesis topic by itself. The complexity, and multivariate nature of this concept made the exploratory case study only a small attempt at the analysis of its nature. In order to uncover more details, another study could look at the particular aspects of DRL implementation, data requirements, integration with the current practices, as well as the stages of the application development. Specifically the last factor could be evaluated in great detail. This is because of the nature of the DRL application and its ability to combine multiple classes of assets within its decision-making capabilities. A thorough research of inspection and maintenance methodologies of various physical assets could provide interesting data, which could then be used to make an informed decision on the necessary features, integration, and stage development.

9.2. Reflection from the MOT perspective

Finalization of the Management of Technology major was not only the motivation behind this Master thesis. This report is a certain culmination, a work that combines knowledge and expertise gained from all the courses of the curriculum. Throughout the two years of the Master courses, MOT provided not only the necessary frameworks and research methods. Most importantly, it helped in reshaping how one thinks about the technology development. Technology creation is not a strictly technical process, on the contrary - it is a multidisciplinary action, which necessitates the understanding of various fields and their interactions. Oftentimes, the context of the innovation must be comprehended first, how it interacts with the world around us, before being able to judge its usability and applicability.

Additionally, by focusing on how companies design and develop products and services to maximize both usability and effectiveness, MOT provides a comprehensive outlook on how technologies work in various contexts. With this in mind, this thesis report attempted to generate a overview on the possible application of Artificial Intelligence technologies and methods, in which their benefits can be defined, communicated, and captured. Technology – the AI – was viewed upon as a material, from which a solution is crafted. Therefore, defining a framework, through which one can analyze the possible gains and benefits of a product based on its adoption, requires the knowledge of emerging innovation development, entrepreneurial practices, and technological impact on the user. Additionally, the specialization package that I had chosen during the course of my studies provided insights into the methods of identifying commercial applications of new technologies, and the role of the possibly involved stakeholders.

9.3. Personal reflection

By doing this research, I was allowed to study the area of technology that fascinates me. Moreover, throughout my two years at MOT, I have realized how important the communication of technology values is. We have a rather hard time understanding the intricacies of the technology that builds the modern day. Especially when considering the Artificial Intelligence, its computational possibilities combined with the great computational power available today, the possibilities are virtually limitless and it is only up to us to find the use cases and implement these solutions. This is also why this topic of research was particularly interesting to me. We have a perfectly adaptable and versatile technology at hand, and practically speaking, the largest obstacle is looking for ways in which we can effectively implement for our benefit.

Looking back at the research processes, I definitely appreciate the possibility of talking to various AI experts and getting to know their views on how the technology adoption process could look like. From the beginning of my studies at the TU Delft MOT, I was intrigued by how the technologies evolve into the solutions we see around us. Therefore the ability to conduct an exploratory case study, where I could investigate a particular application of the DRL algorithms was very rewarding. If I was to do my master thesis research again, I would definitely look in depth on the possibilities that DRL algorithms can offer. It seems that the possibilities are vastly uncovered, as we are still learning about its practical uses. This is probably the most enjoyable part of engineering – trying to figure out where a solution can be used and in what way, discovering new applications, abilities, and purposes.

References

Aalst, W. V., Derksen, G., Schackmann, P., Bouman, F., & Ooijen, W. V. (2015). Automated raveling inspection and maintenance planning on porous asphalt in the netherlands.

Agrawal, A., Gans, J., & Goldfarb, A. (2018). Exploring the impact of artificial intelligence: Prediction versus judgment (no. 24626). *NBER Working Paper, NBER Working Paper. Cambridge, MA.. https://doi. org/10.3386/w24626*.

Allam, S. (2016). The impact of artificial intelligence on innovation-an exploratory analysis. *Sudhir Allam," THE IMPACT OF ARTIFICIAL INTELLIGENCE ON INNOVATION-AN EXPLORATORY ANALYSIS", International Journal of Creative Research Thoughts (IJCRT), ISSN*, 2320–2882.

Anderson, J. C., Kumar, N., & Narus, J. A. (2007). *Value merchants: Demonstrating and documenting superior value in business markets*. Harvard business press.

Anderson, J. C., Narus, J. A., & Van Rossum, W. (2006). Customer value propositions in business markets. *Harvard business review*, *84*(3), 90.

Andrew, M. (2017). The business of artificial intelligence: What it can—and cannot—do for your organization. *Harvard Business Review Digital Articles*, *7*, 3–11.

Andriotis, C., & Papakonstantinou, K. (2018). *Managing engineering systems with large state and action spaces through deep reinforcement learning*.

Andriotis, C., & Papakonstantinou, K. (2020). *Deep reinforcement learning driven inspection and maintenance planning under incomplete information and constraints*.

Arefizadeh, S., & Talebpour, A. (2018). A platooning strategy for automated vehicles in the presence of speed limit fluctuations. *Transportation Research Record*, *2672*(20), 154–161. doi:10.1177/0361198118784176. eprint: https://doi.org/10.1177/0361198118784176

Arts, J., Leendertse, W., & Tillema, T. (2021). Road infrastructure: Planning, impact and management. In R. Vickerman (Ed.), *International encyclopedia of transportation* (pp. 360–372). doi:https://doi.org/10.1016/B978-0-08-102671-7.10448-8

Aslam, B., Karjaluoto, H., & Varmavuo, E. (2021). Data obstacles and privacy concerns in artificial intelligence initiatives. In *Contemporary issues in digital marketing* (pp. 130–138). Routledge.

Aulet, B. (2013). *Disciplined entrepreneurship: 24 steps to a successful startup*. John Wiley & Sons.

Balakrishnan, T., Chui, M., & Henke, N. (2020). Global survey: The state of ai in 2020. *McKinsey Digital*.

Barnes, C., Blake, H., & Pinder, D. (2009). *Creating and delivering your value proposition: Managing customer experience for profit*. Kogan Page Publishers.

Batova, T., Clark, D., & Card, D. (2016). Challenges of lean customer discovery as invention. In *2016 ieee international professional communication conference (ipcc)* (pp. 1–5). IEEE.

Belk, R. (2021). Ethical issues in service robotics and artificial intelligence. *The Service Industries Journal*, *41*(13-14), 860–876.

Belleflamme, P., & Neysen, N. (2020). *A multisided value proposition canvas for digital platforms*. CORE.

Benbya, H., Davenport, T. H., & Pachidi, S. (2020). Artificial intelligence in organizations: Current state and future opportunities. *MIS Quarterly Executive*, *19*(4).

Blank, S., & Dorf, B. (2020). *The startup owner's manual: The step-by-step guide for building a great company*. John Wiley & Sons.

Bleijenberg, A. (2012). The attractiveness of car use. (pp. 19–42). doi:10.1007/978-94-007-2123-4_2

Boddington, P. (2017). *Towards a code of ethics for artificial intelligence*. Springer.

Borges, A. F., Laurindo, F. J., Spínola, M. M., Gonçalves, R. F., & Mattos, C. A. (2021). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. *International Journal of Information Management*, *57*, 102225. doi:10.1016/J.IJINFOMGT.2020.102225

Bostrom, N. (2003). Ethical issues in advanced artificial intelligence. *Science fiction and philosophy: from time travel to superintelligence*, *277*, 284.

Botvinick, M., Ritter, S., Wang, J., Kurth-Nelson, Z., Blundell, C., & Hassabis, D. (2019). Reinforcement learning, fast and slow. *Trends in Cognitive Sciences*, *23*. doi:10.1016/j.tics.2019.02.006

Bower, M., & Garda, R. A. (1985). The role of marketing in management. *McKinsey Quarterly*, *3*(1), 34–46.

Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlstrom, P., … Trench, M. (2017). Artificial intelligence: The next digital frontier?

Cannataro, M., Guzzi, P. H., Agapito, G., Zucco, C., & Milano, M. (2022). Chapter 3 - artificial intelligence. In M. Cannataro, P. H. Guzzi, G. Agapito, C. Zucco, & M. Milano (Eds.), *Artificial intelligence in bioinformatics* (pp. 29–33). doi:https://doi.org/10.1016/B978-0-12-822952-1.00012-7

Carter, M., & Carter, C. (2020). The creative business model canvas. *Social Enterprise Journal*.

Cervero, R. (2014). Transport infrastructure and the environment in the global south: Sustainable mobility and urbanism. *Jurnal Perencanaan Wilayah dan Kota*, *25*, 174–191. doi:10.5614/jpwk.2015.25.3.1

Chang, A. C. (2020a). Chapter 1 - basic concepts of artificial intelligence. In A. C. Chang (Ed.), *Intelligence-based medicine* (pp. 7–22). doi:https://doi.org/10.1016/B978-0-12-823337-5.00001-9

Chang, A. C. (2020b). Chapter 2 - history of artificial intelligence. In A. C. Chang (Ed.), *Intelligence-based medicine* (pp. 23–27). doi:https://doi.org/10.1016/B978-0-12-823337-5.00002-0

Chengbin, W., Hongbin, W., Min, D., & Yongyan, F. (2022). Lean startup approaches(lsas): Convergence, integration and improvement. *Technological Forecasting and Social Change*, *179*, 121640. doi:https://doi.org/10.1016/j.techfore.2022.121640

Clayton, V. (1983). Wisdom and intelligence: The nature and function of knowledge in the later years. *The International Journal of Aging and Human Development*, *15*(4), 315–321.

Copeland, B. J., & Proudfoot, D. (2007). - artificial intelligence: History, foundations, and philosophical issues. In P. Thagard (Ed.), *Philosophy of psychology and cognitive science* (pp. 429–482). doi:https://doi.org/10.1016/B978-044451540-7/50032-3

Cresswell, T. (2010). Towards a politics of mobility. *Environment and Planning D-society Space - ENVIRON PLAN D-SOC SPACE*, *28*, 17–31. doi:10.1068/d11407

da Luz Peralta, C. B., Echeveste, M. E. [Marcia Elisa], Martins, V. L. M., & Lermen, F. H. (2020). Applying the framework to identify customer value: A case of sustainable product in agriculture. *Journal of Cleaner Production*, *270*, 122384. doi:https://doi.org/10.1016/j.jclepro.2020.122384

da Luz Peralta, C. B., Echeveste, M. E. [Márcia Elisa], Lermen, F. H., Marcon, A., & Tortorella, G. (2020). A framework proposition to identify customer value through lean practices. *Journal of Manufacturing Technology Management*.

Darvishvand, F., & Latifi, M. (2021). *A deep reinforcement learning model for predictive maintenance planning of road assets: Integrating lca and lcca*.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319–340.

Dennis, L. (2018). *Value propositions that sell*. eBook Partnership.

Desouza, K. C., Dawson, G. S., & Chenok, D. (2020). Designing, developing, and deploying artificial intelligence systems: Lessons from and for the public sector. *Business Horizons*, *63*(2), 205–213.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of big data – evolution, challenges and research agenda. *International Journal of Information Management*, *48*, 63–71. doi:https://doi.org/10.1016/j.ijinfomgt.2019.01.021

El Bouchefry, K., & de Souza, R. S. (2020). Chapter 12 - learning in big data: Introduction to machine learning. In P. Škoda & F. Adam (Eds.), *Knowledge discovery in big data from astronomy and earth observation* (pp. 225–249). doi:https://doi.org/10.1016/B978-0-12-819154-5.00023-0

Erkens, S., Vliet, D., Ven, M., Voskuilen, J., R.Hofman, J.Jager, & The, P. (2015). On the need for innovation in road engineering - a dutch example-.

Etzioni, A., & Etzioni, O. (2017). Incorporating ethics into artificial intelligence. *The Journal of Ethics*, *21*(4), 403–418.

Fagnant, D., & Kockelman, K. (2015). Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice*, *77*. doi:10.1016/j.tra.2015.04.003

Farla, J., Alkemade, F., & Suurs, R. (2010). Analysis of barriers in the transition toward sustainable mobility in the netherlands. *Technological Forecasting and Social Change*, *77*(8), 1260–1269. doi:10.1016/j.techfore.2010.03.014

Fatima, S., Desouza, K. C., & Dawson, G. S. (2020). National strategic artificial intelligence plans: A multi-dimensional analysis. *Economic Analysis and Policy*, *67*, 178–194.

Galaz, V., Centeno, M. A., Callahan, P. W., Causevic, A., Patterson, T., Brass, I., … Levy, K. (2021). Artificial intelligence, systemic risks, and sustainability. *Technology in Society*, *67*, 101741. doi:https://doi.org/10.1016/j.techsoc.2021.101741

Gasparin, M., Quinn, M., Green, W., Saren, M., & Conway, S. (2022). Stories of value: Business model innovation adding value propositions articulated by slow storytelling. *Journal of Business Research*, *149*, 101–111. doi:https://doi.org/10.1016/j.jbusres.2022.04.069

Gebauer, H., Fleisch, E., Lamprecht, C., & Wortmann, F. (2020). Growth paths for overcoming the digitalization paradox. *Business Horizons*, *63*, 313–323. doi:10.1016/J.BUSHOR.2020.01.005

Geels, F. (2006). Multi-level perspective on system innovation: Relevance for industrial transformation. (pp. 163–186). doi:10.1007/1-4020-4418-6_9

Geels, F. W., Sovacool, B. K., Schwanen, T., & Sorrell, S. (2017). The socio-technical dynamics of low-carbon transitions. *Joule*, *1*(3), 463–479. doi:https://doi.org/10.1016/j.joule.2017.09.018

Ghezzi, A. (2020). How entrepreneurs make sense of lean startup approaches: Business models as cognitive lenses to generate fast and frugal heuristics. *Technological Forecasting and Social Change*, *161*, 120324. doi:https://doi.org/10.1016/j.techfore.2020.120324

Ghosh, B., Daugherty, P. R., Wilson, H. J., & Burden, A. (2019). Taking a systems approach to adopting ai. *Harv Bus Rev May*.

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, *14*(2), 627–660.

Golding, L. P., & Nicola, G. N. (2019). A business case for artificial intelligence tools: The currency of improved quality and reduced cost. *Journal of the American College of Radiology*, *16*(9), 1357–1361.

Goodwin, P. (2013). Peak travel, peak car and the future of mobility. (pp. 53–89). doi:10.1787/9789282105931-3-en

El-Haddadeh, R., Osmani, M., Hindi, N., & Fadlalla, A. (2021). Value creation for realising the sustainable development goals: Fostering organisational adoption of big data analytics. *Journal of Business Research*, *131*, 402–410.

Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda□. *Technological Forecasting and Social Change*, *162*, 120392.

Han, C., Ma, T., & Chen, S. (2021). Asphalt pavement maintenance plans intelligent decision model based on reinforcement learning algorithm. *Construction and Building Materials*, *299*, 124278. doi:https://doi.org/10.1016/j.conbuildmat.2021.124278

Han, C., Ma, T., Xu, G., Chen, S., & Huang, R. (2020). Intelligent decision model of road maintenance based on improved weight random forest algorithm. *International Journal of Pavement Engineering*, 1–13. doi:10.1080/10298436.2020.1784418

Harvey, H. B., & Gowda, V. (2021). Regulatory issues and challenges to artificial intelligence adoption. *Radiologic Clinics of North America*, *59*(6), 1075–1083. Artificial Intelligence in Radiology. doi:https://doi.org/10.1016/j.rcl.2021.07.007

Hodson, H. (2019). Deepmind and google: The battle to control artificial intelligence. *The Economist, ISSN*, 0013–0613.

Hofmann, P., Oesterle, S., Rust, P., & Urbach, N. (2019). *Machine learning approaches along the radiology value chain - rethinking value propositions*.

Hogan, T., & Zhou, Q. (2010). Defining university spin-offs. *New Technology Based Firms in the New Millennium*, *8*, 7–23. doi:10.1108/S1876-0228(2010)0000008004

Huang, J., Chang, Q., & Arinez, J. (2020). Deep reinforcement learning based preventive maintenance policy for serial production lines. *Expert Systems with Applications*, *160*, 113701. doi:https://doi.org/10.1016/j.eswa.2020.113701

Jeekel, J. (2015). The future of car mobility 2014-2030 ; material for a debate on framing smart mobility. *Journal of Traffic and Transportation Engineering*, *3*(3), 166–177. doi:10.17265/2328-2142/2015.03.005

Johnson, E. (2012). Business model generation: A handbook for visionaries, game changers, and challengers - by alexander osterwalder and yves pigneur. *Journal of Product Innovation Management*, *29*.

Johnson, K., Pasquale, F., & Chapman, J. (2019). Artificial intelligence, machine learning, and bias in finance: Toward responsible innovation. *Fordham L. Rev.*, *88*, 499.

Kambil, A., Ginsberg, A., & Bloch, M. (1996). Re-inventing value propositions.

Kaplan, A., & Haenlein, M. (2020). Rulers of the world, unite! the challenges and opportunities of artificial intelligence. *Business Horizons*, *63*(1), 37–50.

Kemp, R., Blythe, P., Brace, C., James, P., Parry-Jones, R., Thielens, D., … Urry, J. (2010). Electric vehicles:charged with potential.

Khan, S. A., & Bohnsack, R. (2020). Influencing the disruptive potential of sustainable technologies through value proposition design: The case of vehicle-to-grid technology. *Journal of Cleaner Production*, *254*, 120018.

Kiran, B., Sobh, I., Talpaert, V., Mannion, P., Sallab, A., Yogamani, S., & Perez, P. (2021). Deep reinforcement learning for autonomous driving: A survey. *IEEE Transactions on Intelligent Transportation Systems*, *PP*, 1–18. doi:10.1109/TITS.2021.3054625

Konya-Baumbach, E., Schuhmacher, M. C., Kuester, S., & Kuharev, V. (2019). Making a first impression as a start-up: Strategies to overcome low initial trust perceptions in digital innovation adoption. *International Journal of Research in Marketing*, *36*(3), 385–399. Marketing Perspectives on Digital Business Models. doi:https://doi.org/10.1016/j.ijresmar.2019.01.008

Laage-Hellman, J., Landqvist, M., & Lind, F. (2018). Business creation in networks: How a technology-based start-up collaborates with customers in product development. *Industrial Marketing Management*, *70*, 13–24. Change in business relationships and networks: Concepts and business reality. doi:https://doi.org/10.1016/j.indmarman.2017.07.009

Lanning, M. J. (1998). *Delivering profitable value*. Perseus Books Group Cambridge.

Lanning, M. J., & Michaels, E. G. (1988). A business is a value delivery system. *McKinsey staff paper*, *41*(July).

Le, H. V., & Suh, M.-h. (2019). Changing trends in internet startup value propositions, from the perspective of the customer. *Technological Forecasting and Social Change*, *146*, 853–864. doi:https://doi.org/10.1016/j.techfore.2018.06.021

Li, R., Zhao, Z., Zhou, X., Ding, G., Chen, Y., Wang, Z., & Zhang, H. (2017). Intelligent 5g: When cellular networks meet artificial intelligence. *IEEE Wireless communications*, *24*(5), 175–183.

Lichtenthaler, U. (2019). An intelligence-based view of firm performance: Profiting from artificial intelligence. *Journal of Innovation Management*, *7*, 7. doi:10.24840/2183-0606_007.001_0002

Linde, L., Sjödin, D., Parida, V., & Gebauer, H. (2021). Evaluation of digital business model opportunities: A framework for avoiding digitalization traps. *Research-Technology Management*, *64*, 43–53. doi:10.1080/08956308.2021.1842664

Mallick, R. (2016). Understanding the impact of climate change on pavements with cmip5, system dynamics and simulation. *International Journal of Pavement Engineering*, *19*. doi:10.1080/10298436.2016.1199880

Marchesi, L., Marchesi, M., Tonelli, R., & Lunesu, M. I. (2022). A blockchain architecture for industrial applications. *Blockchain: Research and Applications*, 100088. doi:10.1016/J.BCRA.2022.100088

Margaret Taylor, A. T. (2012). The technology life cycle: Conceptualization and managerial implications. *International Journal of Production Economics*, *140*, 541–553. doi:10.1016/J.IJPE.2012.07.006

Marović, I., Androjić, I., Jajac, N., & Hanak, T. (2018). Urban road infrastructure maintenance planning with application of neural networks. *Complexity*, *2018*. doi:10.1155/2018/5160417

Meske, C., Bunde, E., Schneider, J., & Gersch, M. (2022). Explainable artificial intelligence: Objectives, stakeholders, and future research opportunities. *Information Systems Management*, *39*(1), 53–63.

Miernicki, M. et al. (2021). Artificial intelligence and moral rights. *AI & SOCIETY*, *36*(1), 319–329.

Minshall, T., & Wicksteed, B. (2005). University spin-out companies: Starting to fill the evidence gap.

Mnih, V., Kavukcuoglu, K., Silver, D., Graves, A., Antonoglou, I., Wierstra, D., & Riedmiller, M. (2013). Playing atari with deep reinforcement learning.

Moorman, R., Frownfelter, J., Wretling, S., Price, S., & Taraman, S. (2020). Basic concepts of artificial intelligence. *Intelligence-Based Medicine: Artificial Intelligence and Human Cognition in Clinical Medicine and Healthcare*, 7–22. doi:10.1016/B978-0-12-823337-5.00001-9

Moriarty, P., & Honnery, D. (2008). Low-mobility: The future of transport. *Futures*, *40*, 865–872. doi:10.1016/j.futures.2008.07.021

Muthukrishnan, N., Maleki, F., Ovens, K., Reinhold, C., Forghani, B., & Forghani, R. (2020). Brief history of artificial intelligence. *Neuroimaging Clinics of North America*, *30*(4), 393–399. Machine Learning and Other Artificial Intelligence Applications. doi:https://doi.org/10.1016/j.nic.2020.07.004

Nelson, G. S. (2019). Bias in artificial intelligence. *North Carolina medical journal*, *80*(4), 220–222.

Nenonen, S., Storbacka, K., Sklyar, A., Frow, P., & Payne, A. (2020). Value propositions as market-shaping devices: A qualitative comparative analysis. *Industrial Marketing Management*, *87*, 276–290. doi:https://doi.org/10.1016/j.indmarman.2019.10.006

Newbert, S. L., Tornikoski, E. T., & Augugliaro, J. (2020). To get out of the building or not? that is the question: The benefits (and costs) of customer involvement during the startup process. *Journal of Business Venturing Insights*, *14*, e00209. doi:https://doi.org/10.1016/j.jbvi.2020.e00209

Nguyen, H., & La, H. (2019). *Review of deep reinforcement learning for robot manipulation*. doi:10.1109/IRC.2019.00120

Osterwalder, A. (2014). Value proposition design : How to create products and services customers want : Get started with. *How to create products and services customers want*.

Ouchchy, L., Coin, A., & Dubljević, V. (2020). Ai in the headlines: The portrayal of the ethical issues of artificial intelligence in the media. *AI & SOCIETY*, *35*(4), 927–936.

Pais, J., Figueiras, H., Pereira, P., & Kaloush, K. (2018). The pavements cost due to traffic overloads. *International Journal of Pavement Engineering*, *20*, 1–11. doi:10.1080/10298436.2018.1435876

Panch, T., Mattie, H., & Atun, R. (2019). Artificial intelligence and algorithmic bias: Implications for health systems. *Journal of global health*, *9*(2).

Payne, A., Frow, P., Steinhoff, L., & Eggert, A. (2020). Toward a comprehensive framework of value proposition development: From strategy to implementation. *Industrial Marketing Management*, *87*, 244–255. doi:10.1016/J.INDMARMAN.2020.02.015

Perc, M., Ozer, M., & Hojnik, J. (2019). Social and juristic challenges of artificial intelligence. *Palgrave Communications*, *5*(1), 1–7.

Piepponen, A., Ritala, P., Keränen, J., & Maijanen, P. (2022). Digital transformation of the value proposition: A single case study in the media industry. *Journal of Business Research*, *150*, 311–325. doi:https://doi.org/10.1016/j.jbusres.2022.05.017

Reim, W., Åström, J., & Eriksson, O. (2020). Implementation of artificial intelligence (ai): A roadmap for business model innovation. *AI*, *1*(2), 11.

Rejewski, M. (1980). Jak matematycy polscy rozszyfrowali enigme. *Annales de*.

Richbourg, R. F. (2018). *Deep learning: Measure twice, cut once*. Institute for Defense Analyses. Retrieved from http://www.jstor.org/stable/resrep36394

Ries, E. (2016). The lean startup by eric ries. *The Starta*.

Rietveld, P., Bruinsma, F., & Koetse, M. (2007). Infrastructure maintenance costs: A comparison of road, rail and inland navigation. In OECD (Ed.), *Estimation and evaluation of transport costs* (pp. 49–76). OECD.

Rintamaki, T. (2007). H, & mitronen, I.(2007). identifying competitive customer value propositions in retailing. *Managing Service Quality*, *17*(6).

Rossi, F. (2018). Building trust in artificial intelligence. *Journal of international affairs*, *72*(1), 127–134.

Russell, S., Hauert, S., Altman, R., & Veloso, M. (2015). Ethics of artificial intelligence. *Nature*, *521*(7553), 415–416.

Saw, S. N., & Ng, K. H. (2022). Current challenges of implementing artificial intelligence in medical imaging. *Physica Medica*, *100*, 12–17.

Sharma, M., Luthra, S., Joshi, S., & Kumar, A. (2021). Implementing challenges of artificial intelligence: Evidence from public manufacturing sector of an emerging economy. *Government Information Quarterly*, 101624. doi:https://doi.org/10.1016/j.giq.2021.101624

Siau, K., & Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics. *Cutter business technology journal*, *31*(2), 47–53.

Simmonds, D., & Bhattacherjee, A. (2014). Green it adoption and sustainable value creation.

Sjödin, D., Parida, V., Jovanovic, M., & Visnjic, I. (2020). Value creation and value capture alignment in business model innovation: A process view on outcome-based business models. *Journal of Product Innovation Management*, *37*(2), 158–183.

Sjödin, D., Parida, V., Kohtamäki, M., & Wincent, J. (2020). An agile co-creation process for digital servitization: A micro-service innovation approach. *Journal of Business Research*, *112*, 478–491. doi:10.1016/J.JBUSRES.2020.01.009

Sjödin, D., Parida, V., Palmié, M., & Wincent, J. (2021). How ai capabilities enable business model innovation: Scaling ai through co-evolutionary processes and feedback loops. *Journal of Business Research*, *134*, 574–587. doi:10.1016/J.JBUSRES.2021.05.009

Smith, A. M., & Green, M. (2018). Artificial intelligence and the role of leadership. *Journal of Leadership Studies*, *12*(3), 85–87.

Stern, A. D. (2022). Overcoming legal liability obstacles to ai adoption. *NEJM Catalyst Innovations in Care Delivery*, *3*(3).

Sun, T. Q., & Medaglia, R. (2019). Mapping the challenges of artificial intelligence in the public sector: Evidence from public healthcare. *Government Information Quarterly*, *36*(2), 368–383.

Tarafdar, M., Beath, C. M., & Ross, J. W. (2019). Using business ai to operations enhance. *MIT Sloan Management Review*, *60*.

Taylor, S. A., Hunter, G. L., Zadeh, A. H., Delpechitre, D., & Lim, J. H. (2020). Value propositions in a digitally transformed world. *Industrial Marketing Management*, *87*, 256–263. doi:https://doi.org/10.1016/j.indmarman.2019.10.004

Triangulation, D. S. (2014). The use of triangulation in qualitative research. In *Oncology nursing forum* (Vol. 41, p. 545).

Trivedi, S., & Patel, N. (2021). The determinants of ai adoption in healthcare: Evidence from voting and stacking classifiers. *ResearchBerg Review of Science and Technology*, *1*(1), 69–83.

Urban, G. L., & Hauser, J. R. (1980). *Design and marketing of new products*. Prentice hall.

Urry, J. (2004). The ‘system’ of automobility. *Theory, Culture Society*, *21*, 25–39. doi:10.1177/0263276404046059

Valle-Cruz, D., Fernandez-Cortez, V., & Gil-Garcia, J. R. (2021). From e-budgeting to smart budgeting: Exploring the potential of artificial intelligence in government decision-making for resource allocation. *Government Information Quarterly*, 101644. doi:https://doi.org/10.1016/j.giq.2021.101644

van Burg, E., Romme, G., Gilsing, V., & Reymen, I. (2008). Creating university spin□offs: A science□based design perspective*. *Journal of Product Innovation Management*, *25*, 114–128. doi:10.1111/j.1540-5885.2008.00291.x

Velu, C. (2018). Coopetition and business models. In *The routledge companion to coopetition strategies* (pp. 336–346). Routledge.

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, *122*, 889–901. doi:10.1016/J.JBUSRES.2019.09.022

Volkmar, G., Fischer, P. M., & Reinecke, S. (2022). Artificial intelligence and machine learning: Exploring drivers, barriers, and future developments in marketing management. *Journal of Business Research*, *149*, 599–614.

Wirtz, B. W., Weyerer, J. C., & Geyer, C. (2019). Artificial intelligence and the public sector—applications and challenges. *International Journal of Public Administration*, *42*(7), 596–615.

Yin, R. K. (2012). Case study methods.

Zuiderwijk, A., Chen, Y.-C., & Salem, F. (2021). Implications of the use of artificial intelligence in public governance: A systematic literature review and a research agenda. *Government Information Quarterly*, *38*(3), 101577. doi:https://doi.org/10.1016/j.giq.2021.101577

A

Questionnaire for the empirical study interviews

1. Can you define your area of expertise regarding the Artificial Intelligence technology?
2. What do you define as an Artificial Intelligence solution?
3. What is, in your perspective, the main advantage of Artificial Intelligence solutions?
4. What is, in your perspective, the most significant factor preventing the adoption of AI solutions?
5. Did you ever encounter data availability or integration issues? Is there influence of data availability, quality, or adaptability for the AI implementation?
6. How can Artificial Intelligence be integrated with other solutions? How important is the factor of compatibility; what are the obstacles?
7. How demanding is the process of AI implementation in your perspective?
8. What influence can AI have on the surrounding stakeholders?
9. What previous experiences allow for the AI application? What experiences ease the adoption of AI solutions?

10. How do you perceive the costs and benefits of AI applications? How can we quantify these aspects?

11. What financial benefits can AI offer?

12. How are AI solutions different from other methods available?

13. What role does the organization play in the AI solution integration? Can you mention any ‘human factors’?

14. What is the importance of leadership support in the AI adoption process?

15. How can we ‘trust’ the AI? What in your perspective are the factors that affect the confidence in AI solutions?

16. What can be done to manage bias towards AI applications?

17. What are some of the concerns regarding AI technologies? How can they affect AI adoption?

18. What other factors can affect the adoption of Artificial Intelligence solutions? Any aspects that should be added?

19. What is your view on the grouping of these factors in the conceptual model?

B

Confidentiality clause

Dear Participant,

Thank you for agreeing to participate in the research study for the Master Thesis of Management of Technology (TPM Department, Delft University of Technology) regarding the adoption of Artificial Intelligence and subsequent Value Proposition design. This document describes the research goals and defines the confidentiality and privacy aspects.

The goal of the research is to define and evaluate the factors responsible for the adoption of Artificial Intelligence solutions, across multiple domains and applications. Furthermore, the AI adoption process is translated into value proposition design, which specifies the aspects of the solution that should be considered for the implementation of a new AI product. Additionally, the AI value proposition is viewed from the perspective of the Value Proposition Creation model, often used by University Spin-Offs. An exploratory case study is carried out, which tests the assumptions and analyzes the application of Deep Reinforcement Learning decision-making algorithm in the field of road maintenance and inspection planning.

To achieve the goals, a series of semi-structured expert interviews is carried out. The participation in the interview is voluntary, and all necessary measures are taken to ensure confidentiality and privacy. The interview lasts approximately one hour and can be conducted personally or online, via Zoom/Teams. In either case, the interviewee agrees to record the conversation. The recordings are not considered to be a part of this thesis.

The produced video / voice recordings will be automatically transcribed and manually corrected, if needed. The transcripts will be used for coding purposes, evaluation of the findings, and further research analysis. The transcripts will not be attached to the thesis and they will not be available in the TU Delft Research Repository. To ensure anonymity, your name and personal details will not be stated anywhere in the thesis paper. The video / voice recordings will be deleted after finalization of the research and graduation. Before the research paper is published and the graduation process is finalized, verification of the findings will be made possible.

By signing this document, the participant confirms that they understood the research goals and interview process, and agree with the presented methodology and assurance of confidentiality.

Kind regards,

Tomasz Drozdowski, MOT 5421861

C

Sample VPC definition questions - Value Map

Gain Creators

Use the following trigger questions to ask yourself:

Could your products and services…

1. ... create savings that please your customers? In terms of time, money, and effort.
2. ... produce outcomes your customers expect or that exceed their expectations? By offering quality levels, more of something, or less of something.
3. ... outperform current value propositions and delight your customers? Regarding specific features, performance, or quality.
4. ... make your customers' work or life easier? Via better usability, accessibility, more services, or lower cost of ownership.
5. ... create positive social consequences? By making them look good or producing an increase in power or status.
6. ... do something specific that customers are looking for? In terms of good design, guarantees, or specific or more features.

7. ... fulfill a desire customers dream about? By helping them achieve their aspirations or getting relief from hardship?

8. ... produce positive outcomes matching your customers' success and failure criteria? In terms of better performance or lower cost.

Pain Relievers

Use the following trigger questions to ask yourself:

Could your products and services…

1. ... produce savings? In terms of time, money, or effort.

2. ... make your customers feel better? By killing frustrations, annoyances, and other things that give customers a headache.

3. ... fix under-performing solutions? By introducing new features, better performance, or enhanced quality.

4. ... put an end to difficulties and challenges your customers encounter? By making things easier or eliminating obstacles.

5. ... wipe out negative social consequences your customers encounter or fear? In terms of loss of face or lost power, trust, or status.

6. ... eliminate risks your customers fear? In terms of financial, social, technical risks, or things that could potentially go wrong.

7. ... help your customers sleep better at night? By addressing significant issues, diminishing concerns, or eliminating worries.

8. ... limit or eradicate common mistakes customers make? By helping them use a solution the right way.

9. ... eliminate barriers that are keeping your customer from adopting value propositions? Introducing lower or no upfront investment costs, a flatter learning curve, or eliminating other obstacles preventing adoption.

D

Sample VPC definition questions - Customer Discovery

Customer Gains

1. Which savings would make your customers happy? Which savings in terms of time, money, and effort would they value?
2. What quality levels do they expect, and what would they wish for more or less of?
3. How do current value propositions delight your customers? Which specific features do they enjoy? What performance and quality do they expect?
4. What would make your customers' jobs or lives easier? Could there be a flatter learning curve, more services, or lower costs of ownership?
5. What positive social consequences do your customers desire? What makes them look good? What increases their power or their status?
6. What are customers looking for most? Are they searching for good design, guarantees, specific or more features?
7. What do customers dream about? What do they aspire to achieve, or what would be a big relief to them?

8. How do your customers measure success and failure? How do they gauge performance or cost?

9. What would increase your customers' likelihood of adopting a value proposition? Do they desire lower cost, less investment, lower risk, or better quality?

Customer Pains

1. How do your customers define too costly? Takes a lot of time, costs too much money, or requires substantial efforts?

2. What makes your customers feel bad? What are their frustrations, annoyances, or things that give them a headache?

3. How are current value propositions underperforming for your customers? Which features are they missing? Are there performance issues that annoy them or malfunctions they cite?

4. What are the main difficulties and challenges your customers encounter? Do they understand how things work, have difficulties getting certain things done, or resist particular jobs for specific reasons?

5. What negative social consequences do your customers encounter or fear? Are they afraid of a loss of face, power, trust, or status?

6. What risks do your customers fear? Are they afraid of financial, social, or technical risks, or are they asking themselves what could go wrong?

7. What's keeping your customers awake at night? What are their big issues, concerns, and worries?

8. What common mistakes do your customers make? Are they using a solution the wrong way?

9. What barriers are keeping your customers from adopting a value proposition? Are there upfront investment costs, a steep learning curve, or other obstacles preventing adoption?

Customer Jobs

1. What is the one thing that your customer couldn’t live without accomplishing? What are the stepping stones that could help your customer achieve this key job?

2. What are the different contexts that your customers might be in? How do their activities and goals change depending on these different contexts?

3. What does your customer need to accomplish that involves interaction with others?

4. What tasks are your customers trying to perform in their work or personal life? What functional problems are your customers trying to solve?

5. Are there problems that you think customers have that they may not even be aware of?

6. What emotional needs are your customers trying to satisfy? What jobs, if completed, would give the user a sense of self-satisfaction?

7. How does your customer want to be perceived by others? What can your customer do to help themselves be perceived this way?

8. How does your customer want to feel? What does your customer need to do to feel this way?

9. Track your customer’s interaction with a product or service throughout its lifespan. What supporting jobs surface throughout this life cycle? Does the user switch roles throughout this process?