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Exploring the AI use effects on information evaluation tasks for new product development decision-making

A case study at manufacturing firms that explores the use of AI for decision maker's information evaluation tasks at NPD evaluation gates to improve decision-making.

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Preface

First, a warm welcome to the thesis of *" Exploring the AI use effects on information evaluation tasks for new product development decision-making".* This thesis is written for the purpose to finalise the study of business administration for the specialisation of Innovation & Entrepreneurship at the Radboud University. From the period of January 2020 to August 2020, from which I was privileged to conduct research efforts at leading manufacturers within the Netherlands.

I would like to thank professor R.A.W. Kok sincerely for giving me the chance to investigate a subject that triggered me for a significant period. Especially his thorough criticism, striking suggestions, and ongoing drive pointed me in the right direction within the complex domain of Artificial Intelligence. Further, my gratitude goes to R. Teunissen for securing a practical perspective and for allowing me to participate in his network. Not to mention, my gratefulness to all informants that were prepared to share their experiences on a topic with substantial strategic value.

One last retrospective, I enjoyed all the out of the box conversations with my family and friends about the topic of Artificial Intelligence. Some scenarios might happen in the future; others may remain science fiction forever. The time will tell us!

I wish you a delightful read.

Mauritz Gesink

Nijmegen, August 2020

Abstract

This study explores in what way information derived from AI use does improve decision-making for new product development (NPD). Based on the bounded rationality principles, we designed a multiple case study that explored NPD decision-making improvements through AI use at manufacturing firms. We found two types of AI uses incorporated in NPD decision-making. First, in-machine AI that is an application within the manufacturing machine that create deep learning performance information under real-time customers circumstances. Second, AI analytics that use deep learning on extensive amounts of online customer behaviour data to create future customer preferences of a new market. Research results revealed how these two different AI uses changed the decision-makers information evaluation tasks differently, although both leading to decision-making effectiveness. Still, the effect is conditional as it depends on conditions regarding NPD evaluation gates, decision-making efficiency, and NPD customer orientation. Our study contributes to the bounded rationality theory by demonstrating that both AI uses have different influence on bounded rationality principles. We further contribute by proposing that different types of evaluation gates moderate the AI-related changes leading to decision-making effectiveness. The use of AI analytics further seems to provide more decision-making effectiveness as it supports NPD decision-makers for more focused orientation towards future customers. We offer NPD decision-makers a guide with three steps of consideration to improve NPD decision-making through AI use.

Keywords: Decision-making performance, AI, NPD, evaluation gates, bounded rationality theory

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Chapter 1: Introduction

New Product Development (NPD) can lead to higher growth rates and higher profits for organisations (Cooper, 2019). Nevertheless, to gather success with NPD is risky (Cooper, 2019) and uncertain to predict (Evanschitzky, Eisend, Calantone, & Jiang, 2012). Decision-makers must predict potential failures early on and solve them timely to avoid enforcing resource costs in the next NPD phases (Cooper, 2019). Decision-makers could be confused about how to proceed with this process, from the idea generation until the final commercialisation, because the NPD field argues for opposite information approaches. Some researchers advocate for intuitive styles to include subjectivity for more quality information (Dijksterhuis & Nordgren, 2006; Eling, Griffin, & Langerak, 2013), while others favour analytical styles to adversely reduce information subjectivity for the sake of objective information (Evans, 2008; Kahneman & Klein, 2009). Not surprisingly, confusion exists within the NPD field. Thus, some calls for answers to reduce decision-making errors within the NPD (Eling & Herstatt, 2017).

Artificial Intelligence (AI) could serve as a new perspective to exploit the strengths of both information styles. AI can address extreme complexity and enhance support for human intuition when dealing with uncertainty and equivocality within decision-making (Jarrahi, 2018). NPD case studies indicate that AI could lead to value improvements for the discovery of consumer needs, the identification of high-impact problems, solution finding via online platforms and the selection of NPD solutions (Kakatkar, Bilgram, & Füller, 2020). However, severe constraints of AI include the high complexity of development and operations, leading to high demands of resource costs in time, efforts, and capital (Darko et al., 2020). Moreover, AI information outputs must be sufficiently incorporated within the decision-making process to justify high resource costs (Shah, Horne & Capella, 2012).

1.1 Problem description

The process of the NPD is comprehensive and consists of unstructured and semi-structured development activities (Alvarez & Barney, 2007) with risks and uncertainty. Therefore, the decision-maker needs to evaluate information within the NPD process related to the technology, market, organisation and finance (Mansor, Yahaya, & Okazaki, 2016). On that basis, specific project criteria are defined for each NPD project and afterwards evaluated by making risk predictions (Hewig et al., 2009) or satisfactory trade-offs (Adair, 2019). Decision-makers enhance different information styles for decision-making tasks to reduce errors. Some advocate that decision-making will be more effective by utilising intuitive reasoning through its high amounts of rich information (Eling et al., 2013). Others criticise intuitive subjectiveness (Kahneman & Klein, 2009), and argue that analytical reasoning is more effective as objective information leads to more focused information (Evans, 2008).

Consequently, decision-makers face a paradox when dealing with information for their NPD tasks. Effectiveness requires high quality of information that, in return, helps to increase managerial efficiency, where efficiency decreases when the price of information rises (Fiet, 1996). Thus, requires decision-makers to make trade-offs between maximising information value, by reducing information overload for more efficiency, or through increasing effectiveness of information to achieve higher accuracy (Nonaka, Umemoto, & Senoo, 1996). The more absence of information, the higher the complexity for information evaluation tasks (Julmi, 2019). For example, when the decision-maker is confronted with objectives of different information sources (Hammond, Keeney, & Raiffa, 1998) or perceives high information equivocality, trade-offs become even more complicated. Both leading to fuzziness for decision-makers to understand all possible alternatives (Marques, Gourc, & Lauras, 2011).

Within the area of the information paradox, the use of AI might add significant value for NPD decision-making. Namely through the "system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019, p.15). All these abilities could enhance product performance, internal business operations optimisation, task automation and better decision-making (Davenpoort & Ronanski, 2018). Academic research strengthens this view and state that data-driven leadership and environmental scanning of information lead to more effective NPD (Duan, Cao, & Edwards, 2020).

Still, empirical contributions note that only four per cent of the world-leading companies use AI in their NPD decision-making (Ernst and Young & Microsoft, 2018). Decision-makers struggle to integrate AI within their processes, find it too expensive or do not understand how AI technologies work for their tasks (Davenpoort & Ronanski, 2018). The academical field still does not know how AI and humans can enhance their capabilities together to improve decision-making (Miller, 2019). Thus, researchers ask for new research efforts (Darko et al., 2020; Shah et al., 2012).

1.2 Problem statement

Decision-makers must consider trade-offs in their decision-making style between information effectiveness and information efficiency. The information paradox arises between the reduction of information to achieve decision-making efficiency and simultaneously increase the decision-making effectiveness through accurate information. This research aims to seek if AI information adds value in reducing decision-making errors related to the information challenges within the NPD. Against this background, the central question that motivates this research is: **In what way does Artificial Intelligence information improve decision-making within the New Product Development?**

1.3 Academic relevance

First, this research contributes to the four information limitation principles of the bounded rationality theory (Simon, 1979). The phenomenon of AI use is applied to this theory to explore unknown relationships of AI use for decision-making.

Second, this research adds to the NPD field that tries to reduce decision-making errors to increase decision-making performances. The field explains decision-making errors through decision-makers misbehaviour at evaluation gates (Cooper, 2008) or through inappropriate information approach towards limited information (Dijksterhuis & Nordgren, 2006; Eling et al., 2013; Eliëns, Eling, Gelper, & Langerak, 2018). This research aims to fill a gap of explanations in the field by offering explorative insights for AI use as information approach to reduce decision-making errors. Thereby, answering to the call of Darko et al. (2020) to research AI use for NPD decision-making.

Third, new vital insights could be offered to the literature about information challenges within the NPD stages. Earlier research focused on approaches to deal with ambiguous and complex information challenges (Jespersen, 2012) and information intensity at non-physical evaluation gates (Alam, 2006; Zahay, Griffin & Fredericks, 2004). This research sheds new light on those perspectives using AI for information challenges during the NPD evaluation stages.

1.4 Managerial relevance

This research offers NPD decision-makers to create more understanding of the effects of AI use for their information evaluation tasks to improve decision-making. It provides insights in AI use and the application thereof within different NPD evaluation gates to create decision-making improvements. Further, research findings create an explorative guideline of how AI outputs can be incorporated towards the different information evaluation tasks.

1.5 Scope

This research limits itself to manufacturing organisations within the Dutch industry. Moreover, research restrictions relate to the theoretical lenses of NPD and decision-making. Thus, not meant to investigate in-depth any principles of AI creation, AI programming or specific AI techniques.

1.6 Thesis outline

This research is structured as follows. Chapter two presents the literature of the leading research constructs and the proposed conceptual model for empirical research. Next, in chapter three, the research methodology is explained, on the basis of which chapter four show the main findings. Afterwards, chapter five contains the overall research conclusions, of which chapter six discusses the theoretical contributions, limitations and suggestions for further research and management implications.

Chapter 2: Theoretical background

This chapter specifies within the sections the dimensions of the NPD, decision-making, information tasks and artificial intelligence. The subsections offer research definitions, theories and field discussions. The chapter concludes by presenting the theoretical-driven conceptual model used for the empirical part of this research.

2.1 New product development

NPD literature focuses on the sequence of NPD process activities (Sethi & Iqbal, 2008; Cooper, 1990), different information natures of evaluation gates (Lilien, Morrison, Searls, Sonnack, & Hippel, 2002; Jespersen, 2012; Alam, 2006; Zahay et al., 2004), and topics relating to specific NPD information challenges and performance issues (Ahuja & Lampert, 2001; Todorava & Durisin, 2007; Danneels, 2002; Todorava & Durisin, 2007; Bhuiyan, 2011).

2.1.1 Definition of New product development

The central assumption within the NPD literature is that a newly developed product is the equivalent to its development process. Therefore, the literature explains the final output as a direct result of the development process it has travelled (Prahalad and Hamel, 1990). Most of the research definitions of the NPD have in common that they define a series of development stages as well as evaluation gates (Cooper, 1990; Cooper, 2008; Sethi & Iqbal, 2008; Jespersen, 2012; Tzokas, Hultink, & Hart, 2004). Deviations under NPD researchers occur about the sequence of process activities. Some emphasise a sequential linear process of activities (Cooper, 1990) others criticise linearity because the NPD consists of simultaneous processes of concurrent activities (Sethi & Iqbal, 2008). The non-linear process might better reflect empirical NPD situations, nevertheless, lacks specific generic definitions to secure construct validity. Therefore, this research follows the linear-sequence view of the stage-gate model (Cooper, 2008), that is widely applied in the field and secures comparisons to other influential NPD research better.

In general, the NPD process is the way from idea generation to the final launch of the product (Cooper, 1990). Within the literature, different opinions arise about the types of development activities and whether there are evaluation gates. The BAH model specified seven detailed development activities from new product strategy to commercialisation (Booz, Allen, & Hamilton, 1982); nevertheless, neglect to clarify specific evaluation gates. The stage-gate model of Cooper (2010) does acknowledge specific evaluation gates. That is essential for this research because it is the place where the information paradox for decision-makers occurs. Researchers distinguish non-physical development activities and physical development activities that differentiate in the information natures of information evaluation tasks (Lilien, Morrison, Searls, Sonnack, & Hippel, 2002). Both non-physical and physical development activities will be empirically explored so that this explorative research covers the entire NPD process.

2.1.2 NPD activities

NPD development activities are defined as follows: "a series of stages, where the project team undertakes the work, obtains the needed information, and does the subsequent data integration and analysis" (Cooper, 2008, p. 214). The goal for each stage is to generate the required information to reduce uncertainties and risks and serve as input for the evaluation gates (Cooper, 2008). The evaluation gates function between the development activities to support the decision-maker whether to continue the project and further invest resources or not (Cooper, 2008). That is based on the judgements of decision-makers to prespecified criteria and if these evaluations meet the expectations to make a final decision (Tzokas et al., 2004; Cooper, 2008) that aims to avoid NPD decision errors (Tzokas et al., 2004).

Based on the stage-gate model, the NPD starts with the discovery of new products ideas followed by the initial screen evaluation of whether to commit resources and meet strategic project criteria (Cooper, 1990). The process continues with scoping activities by generating more market and technical information at a low cost in a short time, where a similar second screen is replicated based on more data (Cooper, 1990). The next step is the development stage to build the business case through the generation of customer needs and translate these to development criteria, of which the evaluation gate of the decision on business case evaluate the technical and economic feasibility (Cooper, 2008). That concludes the non-physical development activities, whereafter the development of a prototype gets started, and is evaluated in the post-development review on previously acquired information to criteria of attractiveness (Cooper, 2008). Moreover, validation activities, market tests, and financial analyses generate more information that is afterwards evaluated in the gate of pre-commercialisation business analyses (Cooper, 2008). Then the product is commercialised, whereafter the post-implementation review evaluates the latest data on the performance of the product and can be used as learnings for new products (Cooper, 2008).

2.1.3 NPD evaluation gates

Within the NPD literature, less knowledge is gathered on how decision-makers conduct evaluation gates in detail. For evaluation gates, Cooper (2008) provides a too broad description of both, judgement of deliverables against some prescribed criteria, and the delivery of a decision as output. The decision-making process from an information-based perspective, provides steps of problem exploration, problem selection, solution exploration and solution selection (Katkar et al., 2020), however, lacks to specify these towards the NPD. Therefore, the experimental NPD decision model of Jespersen (2012) fits the research for two-fold: it provides a detailed generic structure for all NPD evaluation gates and offers more in-depth information tasks.

This model specifies six steps of information evaluation tasks. First, the decision-maker starts with the information acquisition that is the selection of NPD activities to generate information for their judgments and choices related to the most relevant information source and rightness of information (Jespersen, 2012). After that, information reception is conducted to receive the right information. Based on that, the decision-maker evaluates information input to assess the generated information on information satisfaction and usefulness (Jespersen, 2012). Afterwards, the decision-maker conducts a project criteria evaluation on applicable information towards the project criteria priorities related to the market, customer, strategy, finance, and technical (Jespersen, 2012). Hereafter, the final decision-making is based on the go/no-go decision within the gate review based on the perceived likelihood of success of the project (Jespersen, 2012). In some cases, the last step is the final feedback of the top management on the decision (Jespersen, 2012).

2.1.4 NPD information challenges

The academical field of NPD gathered substantial insights on different information challenges for non-physical and physical development activities. Compared to physical development activities, non-physical development activities are more information-intensive (Alam, 2006; Zahay et al., 2004). In the non-physical NPD evaluation gates, the decision-maker faces far more ambiguous and complex information than they can handle (Jespersen, 2012). In that situation, the decision-maker tends to use more experience leading to more familiar information sources and familiar activities within the evaluation gates (Henderson and Clarke, 1990). Consequently, they develop a specific subset of information that is often used when facing uncertainty or risks (Ahuja and Lampert, 2001). These information subsets increase the risks of performance traps (Danneels, 2002), information valuation traps (Todorava & Durisin, 2007), market traps (Henderson, 2006) and learning traps (Ahuja & Lampert, 2001). Table 1 list the information challenges derived from the meta-analyses of Bhuiyan (2011) and categorised them into non-physical development, physical development, and post-development activities.

Table 1: Information challenges in the NPD evaluation gates

NPD evaluation gates	Information challenges	Information evaluation methods
Non-physical development	Adopted Bhuiyan (2011) - Generation of potential ideas from internal and external sources - Timely select best projects - Rapid changes in external needs	Adopted Bhuiyan (2011) - Financial analyses - Competitive analyses - Market analyses - Concept testing - Technical feasibility tests - Brainstorming - Gap analyses - Interviews customers - Customer site visits - Lead users
Physical development	Adopted Bhuiyan (2011) - Product design meets objectives - Customer input and feedback - Minimalization development time - Cross-functional collaboration and coordination of resources - Timely identification of problems. - Quick launch of the product - Meet real-time market and customer requirements - Minimise risks due to changing environment	Adopted Bhuiyan (2011) - Customer feedback - A dynamic tool to market - Degree of team cohesiveness - Benchmarks of criteria set - Beta testing
Post-development	Adopted Bhuiyan (2011) - Customer acceptance of the product - Customers level of interest liking, preferences, and intent to purchase - Determining the benefits, attributes and features that lead to customer response - Insights in the usability, performance, and robustness - Formally recording of data to use for appropriate actions to achieve performance	Adopted Bhuiyan (2011) - Product functionality - Customer acceptance - Usability tests

2.1.5 NPD customer orientation

Another important topic within the NPD literature is the different orientations of NPD decision-makers towards current customers or future customers. NPD decision-makers oriented towards future customers are preferably open for new market trends and future customer wishes. In contrast, NPD decision-makers that adopt current customer orientation tries “to understand and satisfy current customers’ needs and wants” (Hillebrand et al., 2011, p. 70). Adopting a customer orientation could decrease the ultimate innovativeness of the NPD (Christensen, 1997), while future market focus can counterbalance this (Hillebrand et al., 2011).

When NPD decision-makers adopt high customer orientation, they are more likely to coordinate NPD resources otherwise allocated for less innovative customer causes (Christensen, 1997). Thus, researchers sometimes argue for more effective future market orientation. Because, NPD decision-maker needs to have attention for emerging needs and future market developments of potential customers (Narver et al., 2004). In the remainder, the following definitions are used to simplify current customer and future customer.

2.2 Decision-making

Decision-making is a highly researched construct within different research fields, thus enhanced different perspectives. One could take different perspectives on decision-making:

- Management (Schoemaker & Russo, 2016; Dean & Sharfman, 1996; Langley, Mintzberg, Pitcher, Posada, & Saint-Macary, 1995);
- Cognition (Kelley & Michela, 1980; Curseu & Vermeulen, 2008;); or
- Computation (Jordan & Mitchell, 2015; Miller, 2019).

This research takes a management perspective because of the NPD decision-making context. Decision-making literature further distinguishes content and process-based efforts (Elbanna, 2006). This research grounds on process-based efforts due to NPD being defined as a process.

2.2.1 Definition of decision-making

"Decision-making is the process whereby an individual, group or organisation reaches conclusions about what future actions to pursue given a set of objectives and limits on available resources." (Schoemaker & Russo, 2016, p. 1). Definitions of decision-making often recall the selection of actions (Curseu & Vermeulen, 2008; Parkin, 1996) and choices of resource allocation (Dean & Sharfman, 1996). From a strategic, perspective decision-making is "committing substantial resources, setting precedents, and creating waves of lesser decisions "(Dean & Sharfman, 1996, p. 379-380). It does identify lesser alternatives, however, fail to specify resource limitations. Decision-making is sometimes defined as the process of information processing activities (Oppenheimer & Kelso, 2015). From a contingency perspective, decision-making is "a mixture of shallow and deep examination of data—generalised consideration of a broad range of facts and choices followed by a detailed examination of a focused subset of facts and choices" (Etzioni, 2001, p. 52). The information paradox in this research assumes two-fold: limits in information resources and the selection of information actions, both mentioned by Schoenmaker & Russo (2016) and therefore applied in this research.

2.2.2 Decision-making effectiveness

If defining decision-making effectiveness as the output of a specific decision, then problem-cause ambiguity may occur (Elbanna, 2006), to avoid that, this research focuses on the identification of decision-making process outputs.

Decision-making effectiveness is "the extent to which a decision achieves the objectives established by management at the time it is made" (Pfeffer & Salancik, 1978, p.372). Other definitions note systematic processes but fail to recognise objective achievement (Drucker, 1967). A more specific NPD related definition is "the selection of projects that fit the firm's strategy and strike the right balance between value and risk “(Van Riel, Semeijn, Hammedi, & Henseler, 2011, p. 765). Even though the latest definition is more NPD focused, it does not recognise different evaluation gates within the NPD, and therefore this research applies the broader definition of Pfeffer & Salancik (1978).

The role of information is critical for reaching decision-making effectiveness because “information about the environment and possible consequences of alternative actions must be acquired and processed (Pfeffer & Salancik 1978, p. 266). To Dean & Sharfman (1996) decision-making effectiveness is reached when the process is:

- Oriented towards achieving appropriate organisational goals.
- Based on accurate information linking of various alternatives to these goals.
- Appreciates and understands environmental constraints.

While rational procedures have a positive effect, political power harms decision-making effectiveness (Dean & Sharfman, 1996). Procedural rationality is related to “the extent to which the decision process involves the collection of information relevant to the decision and the reliance upon analyses of this information in making the choice” (Dean &Sharfman, 1996, p373). Political behaviour defines itself as "activities taken to use power and other resources to obtain one's preferred outcomes in a situation in which there is uncertainty or dissensus about choices” (Allen, Madison, Porter, Renwick, & Mayes, 1979, p. 7). Both elements recently confirmed to be of relevance for decision-making effectiveness (Van den Oever & Martin, 2018).

2.2.3 Decision-making efficiency

Most research lack to precisely define decision-making efficiency from a management perspective. Still this research define decision-making efficiency as, “if the manager is operating in the right operational region leaving the possibility of increasing their performance by de/increasing the inputs/outputs in a determined proportion” (Marco-Serrano, 2006, p. 169). At the same time, the same author recognises another definition as well, “the ability to use the least amount of resources to obtain a set of given outputs” (Marco-Serrano, 2006, p. 169). This research follows the first definition because it allows to measure the efficiency of output and the right operational region of NPD activities. Moreover, earlier research clarified that effectiveness is not possible to reach when it lacks efficient information generation mechanism in the early stages of the process (Dewangan & Godse, 2014). Thus, it indicates that the construct of effectiveness is in some way related to efficiency, where the exact relation will be a subject of this research.

2.2.4 Bounded rationality theory

Decision-making theories differentiate through normative or descriptive perspectives (Lehmann, 1950). This research focuses on descriptive decision-making to explore experiences of decision-making instead of assessing optimal decision-making. Decision-making theories could base on two central assumptions, either rational or non-rational. Rationally based theories are the game theory (Neumann & Morgenstern, 1944) and subjective expected utility theory (Good & Savage, 1955), both not applicable as these do not assume information uncertainty. Non-rational theories like the attribution theory (Kelley & Michela, 1980) and heuristics theory (Moustakas, 1990) focus on individual cognition, while this research focuses on the unit of analyses of organisational NPD decision-making.

This research follows the theory of bounded rationality. Bounded rationality assumes that the decision-maker is unable to possess all information (1979) and therefore, the decision-maker must make choices related to information, that is the fundament of the information paradox. Full information absence within the context of decision-making is explainable through the bounded rationality principles of Simon (1979):

- Incomplete information and inadequate comprehension of the problem nature are always stored within the decision.
- Decision-makers are unable to generate all possible alternative information and consider all of them.
- The evaluation of alternatives is always incomplete, making it impossible to predict all the consequences.
- For the selection of alternatives, the decision criteria of maximisation and optimisation cannot be entirely determined.

2.3 Information evaluation tasks

This section further explores the literature about the information evaluation tasks of decision-making within the NPD. The section's structure is inspired by the NPD decision-making process of Jespersen (2012).

2.3.1 Information generation

Decision-makers choose their information design that can handle the amounts of information and lead to a fit between information and the problem nature (Julmi, 2019). Three decision natures can be distinguished: decision-making under certainty (Cristofaro, 2017), decision-making under risk (Hewig et al., 2009) and decision-making under uncertainty (Bakker, Curseu, & Vermeulen, 2007).

Decision-making under certainty implies full information availability (Cristofaro, 2017), thus not applicable for uncertain NPD decision-making. When confronted with risks, the decision-maker faces incomplete information about available outcomes and must predict alternative outcomes (Hewig et al., 2009), but that is impossible within uncertain situations (Busemeyer & Townsend, 1993; Hewig et al., 2009). The more information absence perceived, the more complex information evaluation tasks become, while information generation can reduce complexity (Julmi, 2019; Adair, 2019). Nevertheless, critics say that information generation is less effective and costly within uncertain situations (Busenitz & Barney, 1997).

2.3.2 Evaluation information input

The problem natures may also differ in the level of ambiguity due to people-driven or task-driven reasons (Sjödin, Frishammar, & Eriksson, 2016; Smith & Lewis, 2011). People driven ambiguity occurs due to different backgrounds, roles, cultures, and lead to different problem interpretations (Sjödin et al., 2016). Task-driven ambiguity occurs from the problem task itself because it contains interconnected, contradictory elements at the same time (Smith & Lewis, 2011). When the problem structures contain large information variety, future problems or consequences cannot be predicted in advance, while low information variety means that the decision-maker is quite sure that future activities will occur (Julmi, 2019). The higher the information variety, the richer information processing is needed to reduce the ambiguity a decision-maker conceives (Daft & Lengel, 1986).

2.3.3 Project criteria evaluation

NPD decision-makers must process information of criteria related to market, customer, strategy, finance, and technical information to weigh priorities of project criteria. Cognitive literature disagrees on whether intuitive reasoning and analytical reasoning follow the same processing logic (Eliëns et al., 2018; Evans, 2013). Modern AI systems follow a dual-processing logic (Jordan & Mitchell, 2015). Thus, this research assumes analytics and intuition as two independent constructs with distinct capacities.

Bounded rationality reasons through ecological rationality that represents the match between the problem nature and task structure (Todd & Gigerenzer 2007). Intuitive reasoning is perceived effective when rich information is needed for information evaluations (Dijksterhuis, 2006; Eling et al., 2013), although negative emotions (Wong & Kwong, 2007) or optimistic overconfidence (Kahneman & Klein, 2009) can lead to misjudgements. Analytical reasoning is perceived as more effective when information evaluations need to secure relevant information (Evans, 2008; Kahneman & Klein, 2009).

2.3.4 Decision-making

When decision-makers confront uncertain situations, they tend to dis-emphasise the value of predictive information (Dew, Read, Sarasvathy, & Wiltbank, 2009). Within risky situations, humans are not good at probabilistic reasoning (Kahnemann & Lovallo, 1993). Therefore, decision-makers can make suboptimal decisions due to complexity. It can overvalue risks due to overly cautious decisions or devalue risk consequences when facing overly risky situations (Hewig et al., 2009). The higher the incomplete information, the riskier situations become (Julmi, 2019). On the other hand, having excessive information leads to more confidence from the decision-maker; however, can restrict the effectiveness of a decision (Hall, Ariss, & Todorov, 2007).

Decision criteria can either be strict or intuitive. Strict decision criteria control the emotions of NPD decision-makers as it reduces the likelihood of overcommitting (Dane & Pratt, 2007; Dijksterhuis, 2006), and above lessens anticipated regret and fear of decision consequences (Wong & Kwong, 2007). Intuitive criteria can weigh the importance of different factors for complex decision criteria (Dijksterhuis. 2006). Nevertheless, it might lead to loss aversion, endowment effect, and status quo bias (Eliëns et al., 2018).

2.4 Artificial Intelligence

Researchers in the field of AI disagree on many topics.

- Debates rise what intelligence is (Wang, 1995; Canhoto & Clear, 2020),
- What AI techniques are (Kaplan & Haenlein, 2019; Wang, 2019; Duan et al., 2019)
- Whether AI capabilities can enhance humans (Miller, 2019; Jarahi,2018; Davenport& Kirby, 2016);
- Lacks confirmation about AI applications for decision-making tasks (Miller, 2019; Davenport & Ronanki, 2018; Sadler-smith & Shefy, 2004))
- If AI should function for automation or augmentation of decision-making (Miller, 2019; Wilson & Daugherty, 2018).

2.4.1 Definition of Artificial Intelligence

Artificial intelligence is the "system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019, p.15). There is no general agreement to define AI within the field (Wang, 2019). Nevertheless, most definitions recognise some capabilities of flexible adaptation (Wang, 1995; Kaplan & Haenlein, 2019; Edwards & Dwivedi, 2019), but define the concepts of learning and intelligence different.

Definitions focus on the types of experience from which learnings are derived that make the system able to adjust to new inputs for human-like tasks (Duan et al., 2019; Norvig & Russel, 2016). AI conceal a broad range of learning techniques and uses, nevertheless this research scopes towards machine learning. Machine learning techniques train algorithms and can range from supervised to unsupervised, or in between by reinforcement learning (Deng, 2014).

The research definition of intelligence is “how it adapts to its environment when operating with insufficient knowledge and resources “(Wang, 1995, p.17). Others define intelligence different as the level of the contingency of the desired input to achieve the ultimate desired output of the system (Canhoto & Clear, 2020). Over the years, researchers described that contingencies of intelligence can relate to information processing types, openness to new information, the real-time operation of various new tasks (Wang, 1995) or available historical information (Canhoto & Clear, 2020).

Due to the broad range of different AI techniques, the use of one specific AI definition is challenging. Therefore, this research follows the abstract definition of Kaplan & Haenlein (2019). That would imply that AI is always self-learning but differ on what basis dependent on the type of intelligent mechanism of flexible adaptation [henceforth: flexible adaptation mechanisms]. Other definitions either lacked to recognise value achievement (Wang, 1995) or present a too abstract definition (Duan, Edwards, & Dwivedi, 2019; Norvig & Russel, 2016).

2.4.2 AI use and NPD decision-making

The literature offers less rigour or statistical evidence-based relationships of AI and organisational decision-making; therefore, the following literature is based on more explorative natures. In general, business literature of AI recognise two-fold advantages for decision-making.

First, AI can "Identify relationships among many factors, which enables human decision-makers to collect and act upon new sets of information more effectively." (Jarrahi, 2018, p. 580).

Second, AI detects “patterns in data and interpreting their meaning using statistically-based machine learning algorithms” (Duan et al., 2019, p. 67). The upcoming sections explore both advantages.

2.4.3 Information generation

Within uncertain and unpredictable situations, the AI can provide support with real-time information generation for human decision-making (Jarahi, 2018). For risky and complex situations, AI has the strength to retrieve and analyse "huge amounts of data, ameliorating the complexity of a problem domain" (Jarrahi, 2018, p. 581). Humans may decide where to generate data, while the AI collect, evaluate, and analyse these data so that the human decision-maker can use this as supportive information for the final decision (Jarrahi, 2018). For ambiguous situations, the role of social networks and building consensus of people's interest is essential (Cross, Borgatti, & Parker, 2002; Parry, Cohen, & Bhattacharya, 2016). AI appears to be weak at understanding the social and political dynamics of ambiguous problems and might only add value through the generation of sentiments and different interpretations (Jarahi, 2018).

2.4.4 Information evaluation input

Until now, it is unclear how AI capabilities enhance human decision-making (Miller, 2019). The analytical reasoning approach of AI fits messy organisational problems insufficient (Jarahi, 2018) and is terrible at tackling information novelties (Guszcza, Lewis, & Evans, 2017). For similar evaluations of information inputs, the use of historical information is often of minimal use for current tasks (Ransbotham, 2016). Because, future information requires intuition that can handle novel or high varying information (Gardner & Martinko, 1996). The NPD decision-making most of the times is based on novel and high varying information, that might become problematic for the use of AI.

2.4.5 Project criteria evaluation

AI discussions relate to different levels of intelligence for the execution of interpretation tasks: support for humans, repetitive task automation, context awareness and learning, or self-awareness (Davenport & Kirby, 2016). AI outputs can express itself in analyses of numbers, words and images, digital task performance and physical task performance (Davenport & Kirby, 2016). For a specific information evaluation task, the AI information must be incorporated (Duan et al., 2020). The higher the intelligence tasks, the harder it is to understand and interpret AI black-box interpretations (Hammond et al., 1998), because it cannot present underlying motivations (Sadler-Smith & Shefy, 2004; Davenport & Ronanki, 2018). That is relevant for this research, as NPD decision-making tasks contain high levels of complexities and uncertainty, thus need higher levels of intelligence to be achieved, that might lead to higher levels of black-box interpretations.

2.4.6 Decision-making

Different opinions occur whether AI decision-making should function for automation or augmentation. Some argue that AI should augment human judgment by providing support rather than automation (Miller, 2019; Wilson & Daugherty, 2018). However, not replace human contributions (Jarrahi, 2018). Because, human intelligence has the unique ability to learn and adapt to new environments and challenges (Duan et al., 2019), others argue for task-dependency as AI can be used for structured decisions (Edwards, Duan, & Robins, 2000).

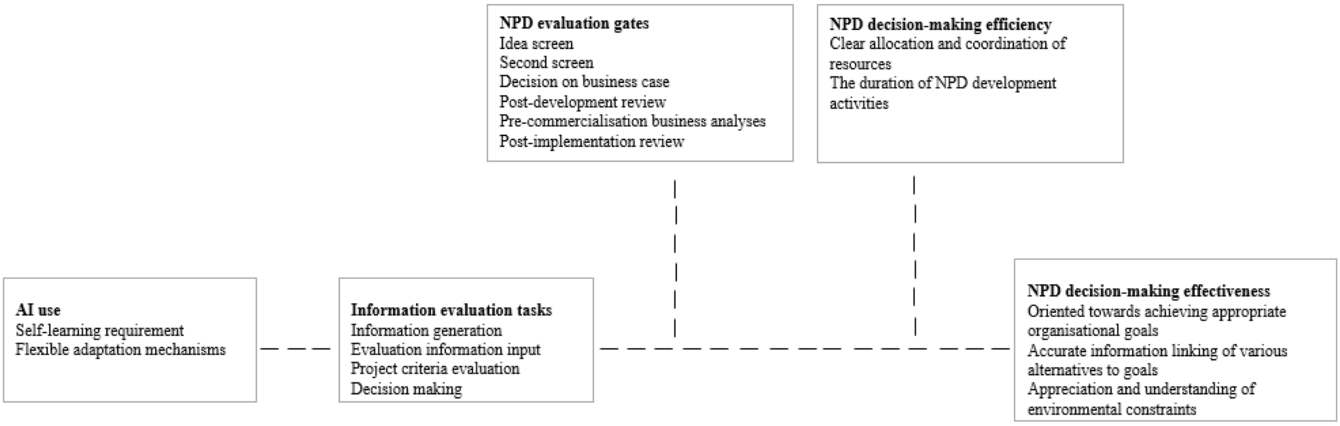
2.4.7 Self-learning AI

AI techniques that use deep learning can learn data patterns without a priori define them (Murphy, 2012), on the condition that it fits with the purpose of the information context (Lee & Shin, 2020). The information input quality can be improved through supervision, ranging from fully supervised to unsupervised training (Deng, 2014). The more supervision, the more accurate the predictions and the higher the costs (Lee & Shin, 2020).

2.5 Conceptual model

The previous literature contributes with insights into decision-making theories and how that relates to the evaluation of information tasks and the NPD. Literature suggests that efficiency might be a moderator for the effectiveness of decision-making. Because, decision-making effectiveness is not achievable when it lacks decision-making efficiency for information generation tasks (Dewangan & Godse, 2014). The research insights of AI within organisational decision-making literature offer limited suggestions of possible AI contributions to decision-making. Most of the attempts assume that AI delivers contributions to the information evaluation tasks for decision-making. Figure 1 shows a suggested conceptual model. We suggest that the use of AI influences the information evaluation tasks, of which related changes affect decision-making effectiveness, while we suggest moderating roles of NPD decision-making efficiency and NPD evaluation gates.

Figure 1:Theoretical-driven conceptual model



The empirical research is designed to explore the theoretical-driven conceptual model. Nevertheless, we secure openness to identify new elements of relevance that had not yet been discovered in literature. Chapter 3 further specifies the choices related to our research design.

Chapter 3: Methodology

Our case study explored the use of AI for NPD decision-making at manufacturing firms. These firms seemed the most advanced with AI use for their NPD (Ernst & Young & Microsoft, 2018).

3.1 Research design

Earlier research did not reveal transparent relationships between AI use and decision-making. This new topic of research has no clear boundaries between the phenomenon and its context, thus needed further exploration. That determined our choice for a qualitative research design that suits explorative research for two-fold. First, the research phenomenon takes place within complex and uncontrolled natures (Yin, 1994) and second, for the research topic's novelty (Barratt, Choi, and Li, 2010). Based on that, we concluded that quantitative research designs like surveys were inappropriate, while experiments were unable to explore phenomena in real-life. Our research followed a design of non-embedded multiple case studies. Thus, appreciates the contextual conditions that are pertinent in the phenomenon of research (Yin, 1994) and allow more exploration of theories in messy real-life situations (Myers, 2013).

From a positivistic perspective, multiple cases increase rigour by "strengthening the precision, the validity and stability of the findings" (Miles & Huberman, 1994, pp. 29), thus, leads to more compelling evidence (Yin, 1994). Our research followed the positivistic research quality criteria consisting of construct validity, internal validity, external validity, and reliability. Nevertheless, case studies lack external validity making it challenging to generalise research results to the whole sampling population (Johnston, Leach, & Liu, 1999). Our case study approach is designed based on the quality principles of positivistic case studies mentioned by Yin (1994). So, our research starts with a clear formulation of the research question, derives logical propositions of theoretical perspectives, use a consistent unit of analyses, link data logically to propositions and interpret findings to specified theoretical criteria.

3.2 Operationalisation

Table 2 presents the research operationalisation that consists of two-fold measure types. First, we adopted academical measurements based on rigorous quantitative research (Sharfman, 1996; Jespersen, 2012), NPD meta-analyses (Dziallas & Blind, 2019), or wide-ranging acceptance in the NPD field (Cooper, 1990). Second, we modified theoretical measurements to fit the research purposes better. Next, the information evaluation process of Jespersen (2012) was simplified to create a better measure of the bounded rationality principles of Simon (1979). We combined the dimensions of information acquisition and information reception into information generation.

The academical measurements of AI are either too broad or still not rigorously validated. When applying the definition of Kaplan & Haenlein (2019), the use of AI always requires a function of self-learning on external data through a mechanism of flexible adaptation. Jarrahi (2018) identified two main flexible adaptation mechanisms for organisational decision-making, the automatic analyses of flexible data from external sources and automatic flexible adaptation based on real-time criteria.

Table 2: Operationalisation research

Construct	Dimensions	Items	Source
NPD decision-making	Effectiveness	- Oriented towards achieving appropriate organisational goals - Accurate information linking of various alternatives to goals - Appreciation and understanding of environmental constraints	Adopted from Dean & Sharfman (1996)
	Efficiency	- Clear allocation and coordination of resources - The duration of NPD development activities	Adopted from Dziallas & Blind (2019)
	NPD evaluation gates	- Idea screen - Second screen - Decision on business cases - Post-development review - Pre-commercialisation business analyses - Post-implementation review	Adopted from Cooper (1990)
Information evaluation tasks	Information generation	- Judgments and choices about the most applicable information source - Receiving the right information	Adapted from Jespersen (2012) and modified inspired by Simon (1979)
	Evaluation information input	- Information satisfaction - Information usefulness	Adopted from Jespersen (2012)
	Project criteria evaluation	- Decision criteria weight priorities	Adopted from Jespersen (2012)
	Decision-making	- Perceived likelihood of success - Go/no go decision on the project idea	Adapted from Jespersen (2012) and modified inspired by Simon (1979)
AI use	Self-learning requirement	- Self-learning information output for continuous improvement	Adopted from Kaplan & Haenlein (2019)
	Flexible adaptation mechanisms	- Automatic analyses of flexible data from external sources - Automatic flexible adaptation based on real-time criteria	Inspired from Jarrahi (2018)

3.3 Case selection

In all cases, the unit of analysis is the firms' NPD decision-making at the R&D department level over the last five years. Our research investigates three different types of cases. Two cases focus on manufacturing firms that use AI within their NPD decision-making, while two manufacturing firms did not. Moreover, two additional cases of AI suppliers were added that developed AI within manufacturing machines for customer firms.

Our research aims for analytical generalisation through the literal replication logic of multiple case selection, because Yin (1994) argues that this establishes limited analytical generalisation of findings. Case research can aim for analytical generalisation of "a particular set of results to some broader theory" (Yin, 1994, p. 36), instead of the statistical generalisation of surveys and experiments. We inspire our case selection on the cross-organisation isomorphism method. This method explains that contextual variables can be considered to make phenomena findings external valid for different contexts (Leung, 2015).

We created case selection criteria as follows. We took NPD FTE as our critical variable to create two different case groups because we expect that NPD FTE has a substantial effect on NPD decision-making. One method is to select similar cases on their independent variables, except the one of interest to the researcher (Seawright & Gerring, 2008). Within the manufacturing firms case groups, we tried to select cases that hold similarities in advanced data use and manufacturing development practices, with one exception of AI use. Next for exploratory purposes, two additional AI supplier cases were selected to confirm or disconfirm the NPD case results. Because, additional cases can strengthen chances to conceive new explorative subject areas (Myers, 2013), thus applied in our research. Table 3 provides specific case contexts based on our case selection criteria. There is no general agreement in the literature on the number of cases (Patton, 1990) and is perceived as a trade-off between breadth and depth (Shakir, 2002). Our literature review suggests that AI use and other types of decision-making contain substantial differences, for example in decision making for real-life messy organisational problems. According to Yin (1994), then three to four unique cases are suitable for literal replication.

Our selection contained four NPD cases and two additional exploratory cases. The NPD organisations were selected on public source knowledge of their advanced data use (Martimes) or their interest in a local AI event for manufacturing companies (CyclingXL, SmartMob, Mechanici, Automatic-AI, AI-impact). A criterium of twenty NPD FTE determined the type of case group, that were asked through preliminary communication with informants. We did not extend the number of cases due to two reasons, the scarce amount of AI cases within the research population and limits on available research resources.

Table 3: Case context

Code	Mechanici	CyclingXL	SmartMob	Martimes	Automatic-AI	AI-impact
Case groups	Multinational group 1	SMEs group 2	Multinational group 1	SMEs group 2	AI supplier group 3	AI supplier group 3
Business activities	Machine developer for electronics	Developer of bicycles	Machine developer for public maintenance	Developer of maritime parts	AI supplier for machine development	AI supplier for machine development
Organisation size	16,000	175	1,500	120	200	11
NPD FTE	80	15	120	4	4	4
NPD activities	Testing & development	Full NPD	Full NPD	Full NPD	Physical NPD activities	Full NPD
Decision-making style	Data-driven	Customer-focused	Customer-focused	Data-driven	N.A.	NA.
Orientation NPD goals	Optimalisation product performance	Fit customer needs	Top-management goals	Optimalisation product performance	NA.	NA.
Information linking of various alternatives	Technical expertise	Technical expertise External customer information	Technical expertise External customer information	Technical expertise Internal customer information	NA.	NA.
Environmental constraints	High variety of data Low available data	Medium variety of data High available data	High variety of data Low available data	Medium variety of data High available data	NA.	NA.
Allocation and coordination resources	Rigid process	Flexible process	Rigid process	Flexible process	NA.	NA.
NPD duration control activities	Deliberate trade-off quality and speed	Template project approval system	Template project approval system	Model to focus on speed of activities	NA.	NA.
Informant position **(Informant code)**	R&D manager (I1A) AI engineer (11B)	R&D manager (I2)	R&D manager (I3)	R&D manager (I4)	R&D Coordinator (I5A) AI engineer (I5B)	Business AI consultant (I6)
Interview duration	I1A:39 minutes I1B:58 minutes	I2:43 minutes	I3:41 minutes	I4:31 minutes	I5A and I5B: 53 minutes	I6:58 minutes

3.4 Data collection

Instead of random sample selection that is common in quantitative research, purposive selection of informants fit our research better. The informants were selected based on their expertise in the fields of NPD or AI. Informants with appropriate experiences secure information of theoretical relevance (Strauss & Corbin, 1990), avoid invalid or meaningless data (Godambe 1982), and maximise the learning from limited samples in data collection (Merriam, 2002). We held interviews with R&D managers and AI engineers with different functional backgrounds to secure more extensive insights concerning AI use and decision-making.

We collected data through seven semi-structured online interviews with eight informants, of which two cases include two informants. Data collection through interviews generates primary data that adds more richness and reliability for a specific purpose (Myers, 2013). We conducted semi-structured interviews instead of structured interviews and questionnaires. Advantages are that semi-structured interview allows room to obtain real-world descriptions of a described phenomenon (Kvale, 1996) while securing new perspectives of the constructs with sufficient theoretical relevance (Symon & Cassell, 2012).

The interview protocols, see Appendix 1, were derived from the structure of the theoretical-driven conceptual model and mastered with two test informants to strengthen data collection. Testing the interview protocol could lead to more in-depth information from interviews (Polkinghorne, 2005). We learned that the NPD process needed to be specified and that we should offer clear introductions when starting a new question group. The interview protocol for NPD cases had the following sequence of questions:

- Question group 1: Introduction of the NPD process, case context.
- Question group 2: Decision-making effectiveness, decision-making efficiency, and evaluation gates.
- Question group 3: AI use, AI use and information evaluation tasks, AI use and decision-making effectiveness.
- Question group 4: AI use and decision-making efficiency, AI use and evaluation gates.

The interviews for AI suppliers followed a different interview protocol, see appendix 1, primarily designed to confirm or disconfirm the earlier NPD case results.

Each interview followed the structure of the interview protocol but allowed informants to determine the flow and content of the discussion, to retrieve more exploratory insights. When necessary, the interviewer asked for clarification of ambiguity or summarised the interpretations of informants. Both to secure correctness of interpretations and allow more in-depth explanations.

3.5 Data analysis

We processed the interview data using procedures of transcribing and reporting data, verification by informants, and whereafter coding took place. Appendix 2 presents the transcripts. Template analyses offer a balance between flexibility and high degrees of analysing structure to secure consistency (Symon & Cassell, 2012). We used template analyses because it strengthened research objectiveness and coding reliability, both specifically tailored to the research requirements of flexibility. That allowed us to explore research themes more extensively to the areas that appeared to store the most relevant data to answer the research question. Template analyses follow combined approaches of bottom-up and top-down (Symon & Cassell, 2012). Accordingly, we used prior themes and thereby allowed room to redefine them afterwards. The primary advantage of template analyses is to secure efficiency within the analyses by working iteratively in applying, modifying, and re-applying the initial template to secure a proper depth-level of analyses (Symon & Cassell, 2012). Appendix 3 offers excel process templates.

Cross-case synthesis can explore empirical results towards the theoretical literature through pattern analyses (Yin, 1994). We applied cross-case synthesis based on our theoretical background by using the following prior themes: NPD decision-making effectiveness, NPD decision-making efficiency, NPD evaluation gates, information generation, evaluation information input, project criteria evaluation, decision-making, AI requirement and flexible adaptation mechanisms. To meet the exploratory nature of our research, we followed three steps of coding. First, we used open codes to consider all possible theoretical directions. Open coding creates a subject-based structure (Richards, 2014) and allows for data-driven sense-making of rich, complex data (Symon, Cassel, 2012). Second, we formed axial codes on prior defined theoretical themes and identified new themes from our data-driven approach and evolved a structure to integrate within our analyses. Third, from previous theory, we derived selective codes whereafter data-driven themes were analysed and searched for new theories that might confirm data-driven findings. That resulted in the identification of the theme NPD customer orientation, and consequential extended our research with NPD customer orientation literature. Triangulation of theories from data-driven selective coding leads to double theoretical confirmation and enhances external validity (Lincoln, 2010).

3.6 Research ethics

We handled according to the ethical guidelines as described within the Master Thesis handbook of Business Administration of Nijmegen School of Management. Concerning the research conduct, treatment of participants, transparency of research goals, withdrawn possibilities for informants, confidentiality and anonymity, and adequate informing of participants and organisation implications of findings. We further declare that we did not conduct plagiarism, fabricate data, manipulate data, misrepresent data, or mismanage data.

Chapter 4: Results

This chapter presents different forms of AI use and specific case contexts of decision-making, followed by the cross-case analyses of possible relationships.

4.1 Description of case context

NPD firms were selected based on their advanced approaches to data use (Maritimes) or from public information of AI use in the firm (Mechanici, SmartMob, CyclingXL). The interviews showed that two case firms (Mechanici, CyclingXL) use AI in NPD activities and two case firms (SmartMob, Maritimes) do not. In the latter two, the informants explained why and what would have happened if AI would have been applied. In addition, two interviews were held with three informants in firms that develop and sell AI applications to customers to further develop their manufacturing machines (henceforth: AI suppliers).

Table 4: The use of AI and its flexible adaptation mechanisms within the cases

	Mechanici	CyclingXL	SmartMob	Maritimes	Automatic-AI	AI-impact
AI use	In-machine application	AI analytics	No	No	In-machine application	In-machine application
Use self-learning function for information output	Deep learning	Deep learning	No	No	Deep learning	Deep learning
Use mechanism of automatic analyses of flexible data from external sources	No	Yes	No	No	No	No
Use mechanism of automatic flexible adaptation based on real-time criteria	Anomaly detection	No	No	No	Anomaly detection	Anomaly detection
Developer of AI	In-house	Third-party	No	No	In-house	In-house

Table 4 shows the AI use within the case studies. Based on our AI research definition, four cases used AI, as these applied a self-learning function to external data, while the others did not. We found evidence within the interviews that the self-learning function is always required to define AI, the Mechanci AI engineer explained *'AI is always self-learning (I1B)'*. Two types of AI use were found in the firms that use AI, which we further use to define two combinations of a self-learning function with different flexible adaptation mechanisms.

First, 'in-machine AI' use combines the self-learning function with the mechanism of automatic flexible adaptation based on real-time criteria. In-machine AI meets our research definition, as the system can interpret real-time performance data of additional sensors in the machine, use deep learning to learn from this data, and use what it learns to generate performance information under real-time customer circumstances through automatic flexible adaptation based on real-time criteria. For example, Mechanici's in-machine AI generates deep learning product performance information through anomaly detection data of real-time machine circumstances for different customers (henceforth: anomaly detection data).

Second, 'AI analytics' use combines the self-learning function with the mechanism of automatic analyses of flexible data from external sources. AI analytics meets our research definition, as the system can interpret public customer data sources, use deep learning to learn from this data, and use what it learns to generate new information of customer or future customer preferences through automatic analyses of flexible data from external sources. For example, CyclingXL used third-party AI analytics that deep learns from a lot of internet browsing behaviour data in America to generate future customer preference information to enter the American market.

Next, a short description of the case contexts is given, with supporting quotes in Appendix three. Table 5 presents the experience-based or expectation-based changes of AI use to the NPD decision-making outputs.

Table 5: The results of AI use-related changes on information evaluation tasks

Case	Mechanici	CyclingXL	SmartMob	Maritimes
Type of AI use	In-machine AI	AI analytics	AI analytics	AI analytics
Provided evidence	Experience-based	Experience-based	Expectation-based	Expectation-based
AI-related changes in Information generation	Yes	Yes	No	Yes
AI-related changes in Evaluation information input	Yes	Yes	No	Yes
AI-related changes in Project criteria evaluation	No	Yes	No	Yes
AI-related changes in Decision-making	No	No	No	No

The forthcoming NPD decision-making outputs from the AI-related changes are presented in Table 6. The how and why of the AI use-related changes affecting the decision-making outputs is further elaborated in the upcoming sections (4.2-4.5). Sections 4.6 and 4.7 presents the conditions for the effect.

Table 6: Decision-making outputs due to AI-related changes

Case Decision-making effectiveness	Mechanici	CyclingXL	SmartMob	Maritimes
Orientation towards achieving appropriate organisational goals	Increase in optimisation product performance goals	Increase in customer needs goals	Decrease in top-management goals	Increase in optimisation product performance goals
Accurate information linking of various alternatives to goals	Increase in linking of performance optimisation alternatives	Increase in linking of future customer preference alternatives	Decrease in linking customer preference alternatives	No explicit effect in linking performance optimisation alternatives
Appreciation and understanding of environmental constraints	Increase in understanding of machine performances in customer circumstances	Increase in understanding future customers preferences	Decrease in understanding customer preferences	No explicit effect in understanding customer constraints
Decision-making efficiency				
Clear allocation and coordination of resources	Decrease in NPD FTE	Decrease in third-party costs	Decrease in NPD FTE	Decrease in NPD FTE
Duration of NPD development activities	Decrease in development time activities	Decrease in development time activities	Decrease in development time activities	Decrease in development time activities

The Mechanici case study concerns the R&D department of a multinational firm that develops cutting machines with in-machine AI applications to meet the NPD goal of product performance optimisation. Deep learning was used to generate new product performance information through acquired data from newly developed sensors in the machine. The main reason for this change was that the firm is active in a complex development ecosystem, with many interconnected firms, leading to machine performance information divided over various ecosystem partners, which complicated suitable product performance information acquisition for further development of cutting machines. Mechanici alternatively developed and integrated in-machine AI use to generate the missing information for the specific post-development review NPD evaluation gate.

Next, a brief process description how Mechanici incorporated in-machine AI use to its NPD information evaluation tasks at the post-development review. The in-machine AI was used for the NPD information generation task to create a new information source of product performance information. That changed the information generation sources and made Mechanici capable of solving previously unsolvable technical issues. The in-machine AI outputs made the evaluation of information inputs more complicated. The AI outputs are black boxes, as they did not offer clear reasons behind the product performance information, which made them hard to interpret or evaluate. That became problematic when trying to develop the machine further towards interpreting customer complaints or adapt to new customer preferences. That is also the reason why in-machine AI use did not change project criteria evaluations nor automate decision-making NPD tasks.

The CyclingXL case entails the entire NPD of a firm that develops adapted bicycles to meet the needs of current and potential customers. The NPD activities focus on meeting customer-need fit goals (henceforth: customer goals) intending to develop bicycles for dealer customers to the preferences of the end-consumer. NPD projects related to customer s primarily use information sources like customer visits and interviews. Recently, sensors were developed that generated a lot of current consumer behaviour data to support future NPD projects. Still this data is minimally used for the NPD and therefore, CyclingXL explores how AI analytics could support the NPD by making better customer preference information out of it. For potential customers, current manual practices of CyclingXL to link customer preference information to alternative NPD projects are inaccurate. The R&D manager ambitioned to start an NPD project to enter the American market for which a third-party AI analytics was used. So that internet behaviour data of potential customers were analysed, which generated insights in unknown customer preferences related to CyclingXL's bicycle products. This resulted in new insights at all non-physical development gates of a new American NPD project.

The AI analytics use were incorporated as follows for the information evaluation tasks. First, the AI analytics output function as a new information generation source to discover hidden customer preferences of potential American customers. Afterwards, the AI analytics output was used to evaluate the information outputs, as it provided the American customer preferences for bicycles used to map specifications for a new product. The AI analytics outputs also changed to external prioritisation of the preferred specifications for achieving the project criteria for a new project. However, the decision-making tasks were not automated.

The case of multinational SmartMob entails the whole NPD of public maintenance machines with a focus on the firm's top management goals. The R&D department is active in a chaotic ecosystem and therefore preferred not to use in-machine AI nor AI analytics. Their NPD projects are technically sophisticated with many unpredictable events. Human expertise and the experience of NPD employees are favoured by the R&D manager to understand customers and link their differing needs to alternatives within the NPD. He beliefs that in-machine AI and AI analytics outputs lack worthy consideration of unpredictable events or cannot consider all of them simultaneously for information evaluation tasks. NPD activities primarily focus on customer s and use information sources like customer visits, dealer visits and participation in industrial steering committees. Those information sources possess highly valued NPD information for NPD decision-making and are hard to access for competitors. These advantages are not present for other external information sources and are therefore deliberately not used within NPD. At the maintenance department of SmartMob, experiments with in-machine AI for predictive maintenance have started aiming to deliver more inclusive services to its customers.

The Maritimes case concerns the whole NPD of the R&D department that works on the development of maritime parts for its goal to optimise performances. Over the years, the R&D manager changed NPD decision-making from more intuitive-based to a more data-driven decision-making style. The consequence is that it combines the expertise sources of maritime employees with academic performance insights from related academic fields. These changes led to new challenges for decision-makers in the firm, as information evaluation tasks require a balance between the FTE efforts and expected gains. Current practices are performed manually by NPD employees, but the R&D manager view AI analytics as a possible development in the future.

The case studies of Automatic-AI and AI-Impact concern AI suppliers that develop and sell personalised AI applications for manufacturing machines and consult about AI incorporation for NPD decision-making. Both AI suppliers apply in-machine AI in close cooperation with customers in NPD projects to optimise performances of manufacturing machines in terms of functionalities, accuracy and speed. Both gather experiences to incorporate in-machine AI into the NPD decision-making of its customers. However, none encountered any customer requests to incorporate AI analytics into NPD decision-making. Both case studies function as a comparison of experiences and expectations with the other case studies.

4.2 Information generation

This section describes whether AI use influences information generation tasks and how AI-related changes affect decision-making effectiveness. The main findings in what way AI-related changes occurred and how that affected decision-making effectiveness are presented in Table 7 and subsections 4.2.1 and 4.2.2 elaborate on the relationships.

Table 7: Results outputs of information generation task

Case:	Mechanici	CyclingXL	SmartMob	Maritimes
AI type	In-machine AI	AI analytics	AI analytics	AI analytics
Evidence	Experience-based	Experience-based	Expectation-based	Expectation-based
Influence of AI use on information generation tasks	Changes in product performance information sources	Changes in new future customers preference sources	No expected changes in ad-hoc sources of customer preferences	Expected changes in product performance sources of academic working principles
Effect of AI-related changes on decision-making effectiveness	Increases decision-making effectiveness	Increases decision-making effectiveness	Lowers decision-making effectiveness	Increases decision-making effectiveness

The following subsections outlines why AI use changed information generation tasks and how these changes influence decision-making effectiveness. It closes with the propositions derived from these results.

4.2.1 Influence of AI use on information generation tasks

We concluded that the use of in-machine AI and AI analytics led to changes in information generation tasks. Both types of AI changed the information sources on which the organisations relied on during the NPD evaluation gates.

<u>*Changes in information generation related to in-machine AI use*</u>

We found that in-machine AI use implied changes in information generation tasks to receive the right product performance information of suitable information sources. That was found in the situation of Mechanci for instance, were the R&D manager decided to change manual real-time test performance tasks of customer circumstances to allow for better information generation for its NPD. The change to in-machine AI demanded new relevant performance data. Thus, real-time sensors were developed for their machines. The R&D manager explained the in-machine AI-related changes in information sources that were necessary to generate real-time test performances: *'Think of the installing of different type of sensors in the machine to generate the relevant data* [anomaly detection data] *from it* [Machine] *that is not yet available'* (I1A, Mechanici). CyclingXL has not yet changed to in-machine AI use despite its sensors generating extensive customer behaviour data. When asked why not, the R&D manager mentioned that changes were needed to create suitable information sources for in-machine AI. He said '*It is a lot of work to set* [data structure] *all that up... If you want to do that* [creation of customer behaviour information source] *with good* [sensor] *data, or preferably with AI, then you must first capture all the data correctly because without good data AI is of no value'* (I2, CyclingXL).

<u>*Changes in information generation related to AI analytics use*</u>

We found that AI analytics could lead to changes in information generation tasks to generate new customer preference information. CyclingXL used AI analytics to generate new customer preference information for the first and second screening gates to explore NPD possibilities for entering the American market. The customer preference information for customer s of active markets was generated by asking for experiences of partnered dealers that sell to bicycle consumers. However, this method was not suitable for American customers, as *'we have a difficult target group* [American cycling people], *where we usually base it* [information generation] *on gut feeling, but what the customer thinks and what we think is usually a huge difference.'* (I2). That was a reason for changing to AI analytics as a substitute source for American preference information generation, to illustrate the consequential information generation changes, *'they* [third-party AI analytics] *find out things that you do not know yourself, and these specific customers may not know either'* (I2, R&D manager).

The expectations of SmartMob's R&D manager differ from the experiences found in the case study of CyclingXL. SmartMob's current practices to generate customer preference information are based on ad-hoc conversations with customer s and partnered dealers. The R&D manager of SmartMob did not think that AI analytics could change its market research practices of information generation. He mentioned the following constraints of AI analytics generation, '*Either the competitor comes with a new feature,* *or I just talk to a customer and identify a customer wish related to a specific characteristic of our product. I have no idea how that is practically possible with AI'* (I3).

4.2.2 Effect of AI use-related changes in information generation on decision-making effectiveness

Here we describe whether and how AI-related changes in information generation lead to changes in decision-making effectiveness. We found that the in-machine AI-related changes in information generation improved the decision-making effectiveness related to optimising the machine. We found that AI analytics-related changes in information generation improved decision-making related to NPD projects aiming to enter a new market with different customers.

<u>*Effect of in-machine AI-related changes on decision-making effectiveness*</u>

We found that in-machine AI-related changes in information generation led to more effective decision-making regarding linking customer performance information to new sophisticated alternatives for meeting machine optimisation goals. In-machine AI-related changes of Mechanici aimed to further optimise the performances of the machine, *'for solving previously unsolvable problems.'* (I1A, R&D manager). Due to the in-machine AI use as an information source, the R&D manager experienced improved decision-making related to optimising the 'weaver' part of the machine, for example *'Think of the alignment of our 'weaver', there were a few weavers that we were not able to develop completely automatic.. therefore, we now use AI, so we can solve these problems.'* (I1A).

<u>*Effect of AI analytics-related changes on decision-making effectiveness*</u>

We found that AI analytics-related changes in information generation led to more effective decision-making regarding linking future customers wishes to new market NPD alternatives for meeting customer goals. AI analytics-related changes aimed to meet potential customers' needs by identifying customer preferences for the NPD project for America. The R&D manager foresees a high potential for the American market: '*The American market is enormous, but the average American cycle relatively less. If you look at the figures of the market, you could sell hundreds or thousands of bicycles, but that does not happen*' (I2, CyclingXL). The AI analytics-related change aimed to effectively generate information to identify the potential of a new American focussed NPD project f. To illustrate how decision-making effectiveness was improved, the R&D manager noticed new groundings for its decision-making, '*by identifying customer wishes of potential customers. Things we do not yet know about our potential customers. (I2)'.*

The R&D manager of SmartMob questions the decision-making effectiveness of AI analytics to meet his NPD top management goals focussed on customer wishes: '*You better have good contact with your customers yourself... I believe that the whole process of product development is much more a business of estimation* [of customer needs] *and a relation-driven process* [personal information sources]'

(I3). Overall, the CyclingXL informant noticed increased decision-making effectiveness effects for AI analytics regarding to potential customers preferences, while the SmartMob informant saw disadvantages for decision-making effectiveness regarding to customer preferences.

4.2.3 Proposition

Using in-machine AI and AI analytics resulted in new information sources for information generation that positively affected the decision-making focus on previously established NPD aims. This leads to proposition 1: *Using in-machine AI and AI analytics changes information generation tasks, which increases decision-making effectiveness.*

4.3 Evaluation information input

This section describes whether AI use influences the evaluation of information input tasks and how AI-related changes affect decision-making effectiveness. Table 8 presents the main findings to further explore the relationships in the subsections 4.3.1 and 4.3.2.

Table 8: Results outputs of evaluation information input task

Case:	Mechanici	CyclingXL	SmartMob	Maritimes
AI type	In-machine AI	AI analytics	AI analytics	AI analytics
Evidence	Experience-based	Experience-based	Expectation-based	Expectation-based
Influence of AI use on evaluation of information input	Changes to evaluations of more black-box customer-related information	Changes to more extensive evaluations of future customers preferences	No expected changes to evaluations of customer and competitor information	Expected changes to evaluations of product performance and customer information
Effect AI-related change on decision-making effectiveness	Lowers decision-making effectiveness	Increases decision-making effectiveness	Lowers decision-making effectiveness	Contingent decision-making effectiveness

The following subsections describe how AI use changed information evaluation tasks and how these changes affect decision-making effectiveness. The section concludes by presenting propositions.

4.3.1 Influence of AI use on information evaluation tasks

We identified that in-machine AI use changed information evaluation inputs to more black-box interpretations when trying to understand the reasons behind machine performance issues. We saw that AI analytics changed information evaluation inputs for better evaluations of future customers preferences.

<u>Changes in evaluation information output related to in-machine AI use</u>

We found that in-machine AI use led to a change towards black-box evaluation information input that led to challenges in customer product performance information. Mechanici's in-machine AI can detect real-time anomalies when used by consumers but sometimes provided incorrect detections, leading to consumer complaints. A consequence of in-machine AI use is the introduction of AI black-box detection inputs for decision-making that changed performance information evaluation input. According to the R&D manager, '*that* [incorrect AI detections] *becomes a problem because you cannot easily reason back why the neural network decided on that outcome in the machine*' (I1, Mechanici).

The AI engineer of Mechanici explained how the black-box input challenged the assessments at the information evaluation input: '*It* [the AI performance input] *is predictive, but not manageable* [for the NPD]*, so if we see that something is wrong, we do not know why it is wrong*' (I1B, Mechanici). Additionally, it became harder to adapt the in-machine AI development to the information evaluations of personal customer development requests. To illustrate the resulting problems, *'To adjust quickly to that* [customer requests] *leads to challenges, and the broader these questions are, the more variation must be considered, and the more difficult it* [information evaluations] *becomes*' (R&D manager, I1A).

Changes in evaluation information output related to AI analytics use

We found that AI analytics use changed the evaluation of information inputs, providing more useful and satisfying future customers preference information. First, CyclingXL used their and dealers' expertise and experience to evaluate the information for a new market. The R&D manager's use of AI analytics changed these tasks by evaluating different future customers preference information inputs. For example, AI analytics '*scanned our website, it has looked at all kind of companies in America that work on similar things, all in a completely automatic manner. The outcome* [of information evaluation inputs] *was that American customers do not search for CyclingXL, but for tricycles with thick tires*' (I2, CyclingXL). The R&D manager found that AI analytics changed his assessment of information input satisfaction and usefulness for future customers preference information, saying: '*Now we know that if we want to succeed in the American market, we must develop a product with thick tires*' (I2, CyclingXL).

On the other hand, we found that both informants of Maritimes and SmartMob did not expect substantial changes in information evaluation inputs due to AI analytics. The R&D manager of Maritimes expects that the input evaluation of the state of the art product working principles of its maritime parts would not be possible with AI analytics. He reasons that actual changes would be contingent on the task, as '*AI systems can anticipate on events* [earlier expertise] *that are already completed and can analyse these to make a prediction. However, no future customer predictions can be provided*' (I4). The SmartMob's R&D manager expects no changes in usefulness or satisfaction for its customer preference information input evaluations by ad-hoc evaluations of customers or employees when considering AI analytics.

4.3.2 Effect of AI use-related changes of information evaluations output on decision-making effectiveness

In this subsection, we describe whether and how AI-related changes in information evaluations input leads to changes in decision-making effectiveness. Our analyses showed that in-machine AI use negatively affects decision-making effectiveness for information evaluation inputs, while AI analytics positively affects this.

Effect of in-machine AI related changes on decision-making effectiveness

We found that in-machine AI-related changes in black-box evaluations of customer complaints and customer preference adaptations led to lower decision-making effectiveness to meet the machine optimisation goal. Changes to black-box interpretations led to more uncertainty of the Mechanici's R&D manager in evaluating customer complaints for what was needed to improve the machine further, "*because if you want to increase the accuracy* [machine performance optimisation] *to a higher level, then you must be able to figure out, invent and troubleshoot why something goes wrong*' (I1A).

The AI engineer confirmed that decreased decision-making effectiveness is directly related to the forthcoming uncertainty of the black box issue. He illustrated the hypothetical situation for Mechanici of which they would overcome the black box issue, '*If you would have data on why a certain problem originates, then you would be able to act on that* [evaluate information input]. *However, that data is a kind of holy grail because if we would have that data, we would have probably found the causes* [to optimise machine performances]' (I1B, Mechanici). The AI engineer told first to overcome the black-box issue for evaluating customer information towards machine optimisation alternatives.

Effect of AI analytics-related changes on decision-making effectiveness

We found that AI analytics-related changes for evaluations of future customers preference information inputs improved decision-making effectiveness to fit customer goals to enter a new market. Before introducing AI analytics at CyclingXL, future customers preference evaluation inputs to enter new markets was not perceived as effective by the R&D manager to meet customer goals: '*There is a lot of data available but gaining specific knowledge from it is the hardest part.*' (I2, R&D manager). To show that previous methods had low decision-making effectiveness, the R&D manager told that they *"have done many analyses* [of market needs]*, but these were always much more positive* [of expected fit bicycles specifications to new market needs] *than in practice*' (I2). The R&D manager tried to improve this by AI analytics-related changes for better understanding of future customers preferences for the American market. The R&D manager experienced more effectiveness in evaluating NPD alternatives to its customer goals, saying '*at once you get insights into the potential dealers you do not know and product specifications that you do not expect*.' (I2).

The R&D manager of SmartMob did not expect improved decision-making for its top-management goals by AI analytics-related changes in evaluation information input: '*Then you just need to know how the existing product are put together and what we once ran into to evaluate what does not work, for* *whatever reason.'* (I3). Again, we found that AI analytics use for information evaluation inputs positively affects decision-making effectiveness when focussing on future customers, while negatively affects when focusing on customers.

4.3.3 Propositions

In-machine AI use could undesirably affect information evaluation inputs for decision-making effectiveness. This leads to proposition 2A: *Using in-machine AI leads changes the evaluation information input, which lowers NPD decision-making effectiveness.*

The use of AI analytics could increase future customer information and provide better support for goal-focussed decisions. This leads to Proposition 2B: *The use of AI analytics changes the evaluation information input, which increases NPD decision-making effectiveness.*

4.4 Project criteria evaluation

This section describes whether AI use influences the project criteria evaluation tasks and how AI-related changes affect decision-making effectiveness. The main findings of the cross-case analyses are presented in Table 9, and further elaborated in the subsections 4.4.1 and 4.4.2.

Table 9: Results outputs of project criteria evaluation task

Case:	Mechanici	CyclingXL	SmartMob	Maritimes
AI type	In-machine AI	AI analytics	AI analytics	AI analytics
Evidence	Experience-based	Experience-based	Expectation-based	Expectation-based
Influence of AI use on project criteria evaluation	No change to evaluations in NPD product performance criteria	Changes in evaluations of more future customer's preference information to product specification criteria	No changes expected in project criteria evaluations.	No changes expected in project criteria evaluations
Effect AI-related change on decision-making effectiveness	Lowers decision-making effectiveness	Increases decision-making effectiveness	Lowers decision-making effectiveness	Contingent decision-making effectiveness

The following sections explain how AI use influenced project criteria evaluation tasks and how these changes affected decision-making effectiveness, leading to propositions.

4.4.1 Influence of AI use on project criteria evaluation tasks

The project criteria evaluations contain the weightings of the decision-maker to prioritize the different project criteria. We found that in-machine AI use for technical performance information did not change the weights of technical criteria evaluations. We found that AI analytics for future customer preferences did changed weights of customer criteria evaluations.

Changes in project criteria evaluations related to in-machine AI use

We found that in-machine AI use did not lead to changes in the weightings of technical performance towards NPD project criteria evaluations. Despite the use of in-machine AI at Mechanci, the R&D manager did not change the NPD technical performance criteria evaluations. The in-machine AI inputs were not used to measure project criteria priorities established up front to weight machine optimisations. The R&D manager said: '*Well it is more anomaly detection, more digital, it does not particularly measur*e [technical performance criteria]' (I1A).

The AI engineer further explained that it is impossible to weight all technical criteria simultaneously with in-machine AI input necessary for future machine optimisation, saying: '*The sci-fi goal of AI is that it can suddenly create a whole blueprint* [all technical performance criteria] *of the machine, but for now that is impossible*' (I1B, Mechanici). The AI engineer mentioned multiple reasons why not to change project criteria evaluations based on in-machine AI inputs: '*You do not know what to measure* [performance optimisation project criteria]*, or it* [in-machine AI] *measure something, and something randomly comes out, or it is too difficult problem that the AI does not know the* [accurate] *outcome either and just tries something to see if it helps*' (I1B).

The AI automation customers' reasoning is often similar to in-machine AI reasons not to change project criteria evaluations: *'It leads to criteria, but the network is very selective on how it makes sense and determines* [weightings of criteria] so *if it meets the criteria, then it* [AI-based weightings] *is right or wrong*' (I5B, AI engineer). Therefore, the in-machine AI outputs are not seen of value by customers due NPD criteria implies levels of uncertainty.

Changes in project criteria evaluations related to AI analytics use

We found that AI analytics use changed NPD project criteria evaluations of weighing future customers preferences against the NPD customer criteria. The regular practices of CyclingXL when starting a new project is to closely cooperate with customers when considering the project criteria: '*Most of them* [project criteria evaluations] *are actually in consultation with our customers with whom the new criteria of our products are drawn up.*' (I2, R&D manager). This approach was not applicable for a new NPD project for a new market with potential customers. Therefore, for the American NPD project the AI analytics substituted this process, leading to external prioritization of customer project criteria: *From that* [AI analytics] *came a list of future customers and the search terms that are important to America for your target group… they* [AI analytics party] *know our customer group and type of product better.'* (I2, R&D manager).

The SmartMob and Maritime R&D managers did not expect AI analytics to change their current project criteria evaluations. The SmartMob R&D manager did not think it could replace human expertise: '*Currently a person has more insights regarding what they should make than the AI system ever will*' (I3). The Maritime R&D manager focussed on human intuition, but did identify one contingency that could lead to a change: *'If you have a lot of* [customer behaviour] *information, you can make models* [for AI analytics] *that are capable of interpreting more than humans can*' (I4).

4.4.2 Effect of AI use-related changes of project criteria evaluations on decision-making effectiveness

In this subsection, we describe whether and how AI-related changes in project criteria evaluations lead to changes in decision-making effectiveness. We found no in-machine AI-related changes and thus no changes in decision-making effectiveness. On the contrary, we found AI analytics-related changes increased decision-making effectiveness by providing better customer criteria weightings to meet customer goals.

<u>*Effect of in-machine AI-related changes on decision-making effectiveness*</u>

We found that in-machine AI use did not lead to any changes in project criteria evaluations, and thus did not affect decision-making effectiveness. At Mechanici, the AI engineer explained why this would not affect decision-making effectiveness for their NPD project criteria: *'Because in the product development, there are thousands of possibilities, and if you are creative almost millions, but what is the right step? Even we do not know that* [optimal weightings of product performance criteria]*, let alone an AI. if we already find it difficult to come up with types of data of which it should learn.'* (IB, Mechanici). The business AI consultant of AI-impact disagrees, seeing the value of AI performance inputs for project performance criteria evaluations to further optimise machines: '*Historical data* [incorrect AI detections] *can serve as a basis to determine which machine specifications must be adapted to prevent it from happening again*' (I6*).*

<u>*Effect of AI analytics-related changes on decision-making effectiveness*</u>

We found that the AI analytics-related changes led to increased decision-making effectiveness for project criteria evaluations, as it improved decision-making orientation for prioritizations of project criteria to customer goals. The AI analytics-related changes of project criteria evaluations made the R&D manager of CyclingXL better able to decide on a better customer fit for the American NPD project. Previous methods for future customers criteria weighting '*was based on gut feeling, but what the future customer thinks, and what we think is most of the times a big difference* [expected and actual preferences]' (I2). The AI-related project criteria evaluations could better weigh the customer fit towards the customer project criteria. The R&D manager explained how these evaluations improved decision-making effectiveness to meet customer goals for the American market: '*Because for the product development, all product requirements and needs were weighted that we did not know before*' (I2).

The R&D manager of SmartMob thought that AI would not lead to better weightings of project criteria for its customer s, due to '*technical reasons* [machine development related]*, and… that the customer just does not want it* [non-rational preferences of product specifications]' (I3). Again, we found different ideas of decision-making effectiveness that can be explained by the differences in customer orientation.

4.4.3 Propositions

No changes of in-machine AI use were found. This leads to proposition 3A: *Using machine AI does not lead to changes in project criteria evaluations that do not affect NPD decision-making effectiveness.*

AI analytics changes NPD project criteria evaluations with more future customer preference understanding for better prioritizations of customer goals. This leads to proposition 3B: *Using AI analytics leads to changes in project criteria evaluations, which positively affect NPD decision-making effectiveness.*

The previous sections show that decision-making effectiveness is assessed positively for future customers but negatively for customers. That leads to Proposition 4: *AI analytics use-related changes that lead to decision-making effectiveness is moderated by the type of NPD customer orientation.*

4.5 Decision-making

This section describes whether AI use influences the decision-making tasks and how AI-related changes affect decision-making effectiveness. The main findings of the cross-case analyses are presented in Table 10, and are further elaborated in the subsections 4.5.1 and 4.5.2.

Table 10: Results outputs of decision-making task

Case:	Mechanici	CyclingXL	SmartMob	Maritimes
AI type	In-machine AI	AI analytics	AI analytics	AI analytics
Evidence	Experience-based	Experience-based	Expectation-based	Expectation-based
Influence of AI use on information generation tasks	No change in perceived likelihood of success for decision-making	No change in perceived likelihood of success for decision-making	No change expected in perceived likelihood of success for decision-making	No change expected in perceived likelihood of success for decision-making
Effect AI-related change on decision-making effectiveness	Lowers decision-making effectiveness	Lowers decision-making effectiveness	Lowers decision-making effectiveness	Lowers decision-making effectiveness

The following subsections describe how AI use changed decision-making tasks, and how AI-related changes affect decision-making effectiveness. This section concludes with the propositions derived from these results.

4.5.1 Influence of AI use on decision-making

All NPD informants agreed that AI use does not lead to changes in decision-making tasks, as AI is not capable of dealing with uncertain information challenges that is important in NPD decision-making.

<u>*Changes in decision-making related to in-machine AI use*</u>

We found that in-machine AI use did not lead to changes in go/no go decisions because it would decrease the decision-makers perceptions of the likelihood of success of a decision. At Mechanici, while in-machine AI use did not change its NPD decision-making, efforts were made in the R&D department to automate real-time operational decision-making of the machine when used by customers. To illustrate the R&D managers opinion on achieving enough likelihood of success for operational decision-making with in-machine AI use: *'From the final control* [machine decision-making] *is the moment were the human comes in.* To *steer the parameters of the machine so he* [machine operator] *can overrule the algorithm. If you want to close* that *loop and take out human participation, we all want that, but then we need to take a few more steps'* (I1A, Mechanici). In-machine operational decision-making contains more fixed elements of relevance for the decision then the NPD decision-making that is more uncertain. The AI engineer explained why in-machine AI use did not lead to changes for Mechanici's NPD decision-making: '*Often, we do not know that* [successful NPD decisions] *ourselves, not to mention doing* [NPD] *decision-making by the AI.'*(I1B).

<u>*Changes in decision-making related to AI analytics use*</u>

For all informants referring to AI analytics, we found that AI analytics use does not lead to changes in go/no go NPD decisions because it decreased the decision-makers perceptions of the likelihood of success of the decision. All earlier information evaluation tasks of CyclingXL were changed by AI analytics use, but the NPD decision-making is still performed manually by NPD employees. Because the R&D manager of CycylingXL perceived AI analytics-related changes for decision-making as less successful: '*It is already hard to connect AI to unstructured data and to say something useful from it* [information evaluation input and project criteria evaluation tasks]*, not to mention AI making a decision for the NPD process.*' (I2). The main reason not to use AI analytics is the perceived likelihood of success of manual decision-making, illustrated by two constraints to not automate a final go/no go decision: '*To actually trust on that* [AI analytics input]*, We do requires a minimum number of hits to rely on , not to forget the basics of our NPD*' (I2).

The business AI consultant of AI-automation does not think that AI analytics could automate, but could support, the NPD decision-making to better assess the likelihood of success: '*Those are complex* *decisions* [combination of evaluation gates] *that are mostly made based on intuition, but if that* [NPD decision-making] *can be further supported by AI, I think that this* [AI analytics] *could make a contribution*' (I5A).

4.5.2 Effect of AI use-related changes of project criteria evaluations on decision-making effectiveness

In this subsection, we describe whether and how AI-related changes in decision-making lead to changes in decision-making effectiveness. We found no changes in decision-making tasks for in-machine AI and AI analytics. We found similar reasons for the lack of decision-making effectiveness related to perceived success of the decision-maker. Perceived success for go/no go decisions of in-machine AI is one of the reasons for Mechanici's machine optimisation goal: '*In some cases, it* [in-machine AI decision-making] *might work quite adequately. However, not in all cases and not with the same reliability as the human can do currently' (I1A, R&D manager).* Likewise, AI analytics-related changes to perceived success for go/no go decisions also lack decision-making effectiveness: *'It would be wise that* [NPD] *decision-making remains a task for people. I think it would be complicated to process personally moral in the computer, nor all environmental factors involved that the computer does not understand yet.'* [I4, R&D manager, Maritimes].

4.5.3 Propositions

The previous subsections lead to proposition 5: *Using in-machine AI and AI analytics does not lead to changes in decision-making, and thus does not affect decision-making effectiveness.*

4.6 Decision-making efficiency

This section describes the moderating role of decision-making efficiency on the effects of AI use-related changes on decision-making effectiveness. Two situations in the case studies of Mechanici and CyclingXL offered these insights. First, the use of in-machine AI to achieve more effective decision-making to optimise the machine performances came at the cost of decision-making efficiency. Second, CyclingXL did not develop in-machine AI in-house because improving the decision-making effectiveness to better fit customer goals required a too high decrease in decision-making efficiency.

4.6.1 Moderator decision-making efficiency for AI-related changes in information evaluation tasks on decision-making effectiveness

For Mechanci's in-house development of in-machine AI, we found that decision-making efficiency decreased when trying to make AI inputs more effective for decisions related to machine optimisation. Conversely, aiming for more decision-making efficiency leads to lower decision-making effectiveness.

Mechanci's R&D manager led the in-house development of in-machine AI and found it hard to apply correctly to achieve the decision-making goal of optimising machine performances. During the in-machine AI development, the R&D manager needed to decide on how much FTE to allocate to meet the desired effectiveness through in-machine AI. He must decide on a trade-off between how many FTE were affordable to meet his effectiveness goal, he illustrated the trade-off as follows: '*Within one afternoon* [low FTE costs] *it is easy to make something that works a bit… But to make it industrially robust, you have to work for a long time* [high FTE costs]' (I1A). The R&D manager required that the in-machine AI meet his goal to improve decision-making for machine optimisation, because '*it is easy to get some efficiency gains, but then it fails sometimes…. A solution* [meeting the goal] *is one that always works*' (I1A). Still, the R&D manager experienced a lack of efficient methods to develop the in-machine AI to a higher accuracy, so he needed to accept lower decision-making efficiency: '*just re-training* [AI] *with a lot of new data, that is one method, but not always the most efficient one*' (I1A).

The second situation is at CyclingXL that use third-party AI analytics, but the R&D manager did not develop an in-house in-machine AI due to high costs. Despite CyclingXL possesses a lot of sensor data, the R&D manager mentioned that in-machine AI use would demand high NPD resources: '*then you will have to record all that data properly, because without good data, AI is of no use to you…, but that is an expensive process*' (I2). Nonetheless, the R&D manager saw in-machine AI's advantages for decision-making effectiveness and meeting his customer goals: '*The recording of data from a bicycle in use, that is very important data, now the development is not really looking at that. But then* [in-machine AI use] *all historical data and the frequently found complaints could be found to support us for solutions within a new product*' (I2).

Despite those advantages, the R&D manager has not yet decided to use in-machine AI due to decision-making efficiency costs: *'It is a lot of work to apply all that, and it is also all relatively new*' (I2). The R&D manager elaborated on the efficiency costs in NPD resources in-machine AI use would demand: '*Actually go through everything* [NPD evaluation gates] *step by step. Fixed documents, fixed data. then you must run through all the* [NPD] *process steps and store data in a certain way so you can find it easily*' (I2). The R&D coordinator of AI-automation mentioned a different challenge among their customers to clearly allocate NPD resources to achieve increased decision-making effectiveness: *'The risk for customers are that it* [the decision-making effectiveness of the AI] *is often such a black box that they do not know what to expect of it. Often it is a high investment, without having any idea what the outcomes are*' (I5A).

4.6.2 Propositions

Increased decision-making effectiveness required more NPD resources, leading to less decision-making efficiency. This leads to proposition 6: *AI analytics and in-machine AI use-related changes that lead to decision-making effectiveness are negatively moderated by decision-making efficiency.*

4.7 NPD evaluation gates

This section explores the moderating role of NPD evaluation gates for AI-related changes in decision-making effectiveness. The results of individual evaluation gates were divided into three categories (see Table 11).

Table 11: The results of the moderating role of evaluation gates on AI-related changes and decision-making effectiveness

		Mechanici	CyclingXL	SmartMob	Maritimes
Categories	**Evidence** **NPD evaluation gates**	Experience	Experience	Expectation	Expectation
Non-physical development	**Idea generation**	No opinion	**Positive** AI analytics to meet customer NPD goals	**Negative** AI analytics to meet customer NPD goals	**Positive** AI analytics to meet customer NPD goals
	Second screen	No opinion	**Positive** AI analytics to meet customer NPD goals	**Negative** AI analytics to meet customer NPD goals	**Positive** AI analytics to meet customer NPD goals
	Decision on the business case	**Negative** In-machine AI on market and customer goals	**Positive** AI analytics to meet customer NPD goals	**Negative** AI analytics to meet customer NPD goals	**Positive** AI analytics to meet customer NPD goals
Physical development	**Post-development review**	**Positive** In-machine AI to meet product performance NPD goals	No opinion	**Negative** No AI use to meet overall NPD goals	No opinion
	Pre-commercialisation business analyses	No opinion	No opinion	No opinion	No opinion
Post-development	**Post-implementation**	**Negative** *I*n-machine AI to meet product performance NPD goals	**Positive** In-machine AI to meet product performance NPD goals	**Positive** In-machine AI to meet product performance NPD goals	**Positive** In-machine AI to meet product performance NPD goals

We asked our informants what influence evaluation gates would have AI use and decision-making effectiveness. We found two moderating effects, one for the non-physical development gates and one for physical development and post-development gate categories. AI analytics increased the decision-making effectiveness more for the non-physical development gates, while in-machine AI increased it more for the physical and post-development gates.

4.7.1 Non-physical development evaluation gates.

Three informants stated that AI analytics-related changes improved decision-making effectiveness more for the non-physical development gates, while none noticed improvements of in-machine AI-related use. The R&D manager of CyclingXL used AI analytics and referred directly to its improving NPD decision-making to customer goals for its non-physical development gates: '*Having an AI algorithm that would search the web would be nice for NPD, because it would find early-on all product requirements and needs that we do not know*' (I2). The Maritime R&D manager has a similar expectation of advantages with AI analytics for non-physical development gates: '*Determining early on what the product should do in terms of requirements. AI* [analytics] *can help us to construct a package on which our whole system would work' (I4).*

The AI engineer of automatic-AI explained why none of the informants saw in-machine AI as useful for non-physical development gates: *'You have to think outside the box to come up with ideas, and so far* [in-machine] *AI is all still inside the box. I do not know if it really applies there. So far, the AI systems I come across have been made very specific*' (I5B). The business consultant of AI-impact explained the difference in AI uses related to the non-physical development gates: '*On one side it* [the in-machine AI] *goes against the outside the box principle, where you think of unknown elements to come up with new things in other areas….. but if you use some data analytics and intelligence* [AI analytics]*, I can imagine that it leads to new directions to focus on'* (I6).

4.7.2 Physical development evaluation gates

We found that in-machine AI-related changes improved decision-making effectiveness for physical development evaluation gates but were not effective for non-physical development gates. Mechanici's in-machine AI-related changes focussed on decision-making effectiveness for the post-development review gate, of which section 4.2 shows that it did led to more effective decision-making that achieve optimisation goals. Despite the advantages for the post-development review gate, it led to less effectiveness for non-physical development gates in meeting the specific requirements of customers: '*For dealing with new requests of the customer… it lead to challenges to fast adapt to that."* (I1A). No informants mentioned substantial effects of AI analytics for both physical development evaluation gates.

4.7.3 Post-development evaluation gates

Seven informants think that in-machine AI-related changes increase decision-making effectiveness for the post-development gate by predictive maintenance. SmartMob's R&D manager was against AI use-related changes to increase decision-making effectiveness, except for predictive maintenance. SmartMob's machines operate for twelve hours a day, and he expects that in-machine AI use could lead to better performance insights of its newly developed machines: '*Predictive maintenance is an important one, so based on the data you receive, you could conclude that certain parts needs replacing'* (I3).

The CyclingXL R&D manager offered a different reason for the decision-making effectiveness of predictive maintenance: 'We *have all the data of our bicycles; when the system* [in-machine AI] *monitors the data it can signal problems and predict which ones will occur*' (I2). However, Mechanici's AI engineer questioned whether this predictive maintenance leads effective decision-making: '*Data that predict how long the machine will have to live by, does not necessarily indicate the reason why this is so, or an area for improvement.*' (I1B).

4.7.4 Propositions

The previous sub-sections lead to the following propositions:

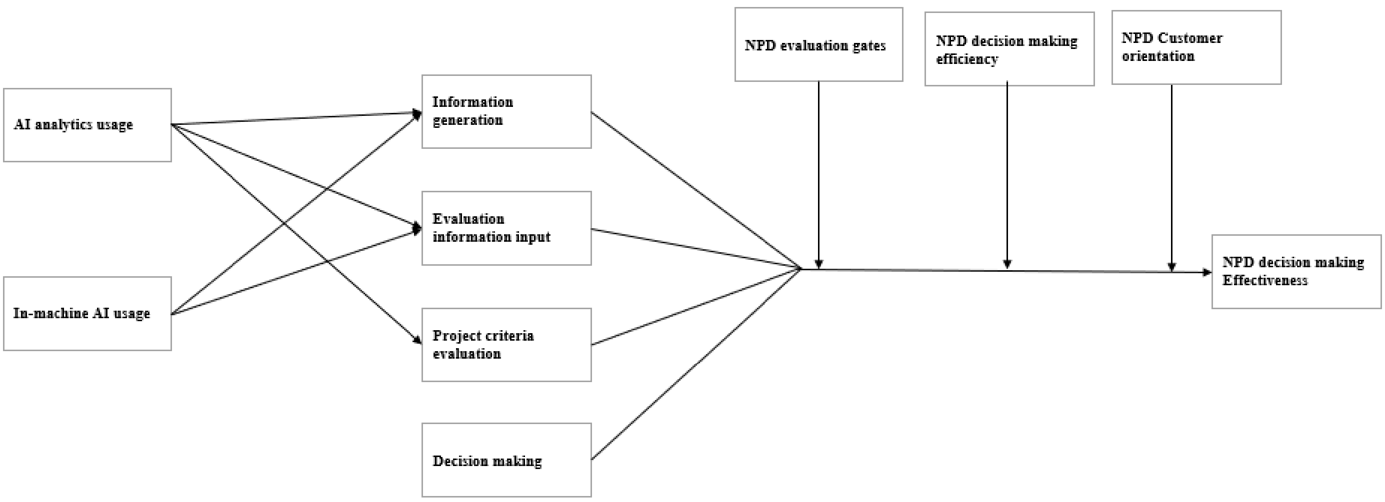
Proposition 7A: The non-physical NPD evaluation gates positively moderate the relationship between using AI analytics and decision-making effectiveness.

Proposition 7B: The post-development NPD evaluation gate positively moderates the relationship between using in-machine AI and decision-making effectiveness.

4.8 Proposed conceptual model

During the interview we found two AI use types: AI analytics and in-machine AI. Based on the theoretical viewpoints and explorative case results, we propose the new conceptual model in Figure 2.

Figure 2: Conceptual model



Chapter 5 Conclusion

In what way does Artificial Intelligence information improve decision-making in the New product development? The NPD decision-maker must make a trade-off between information reduction for decision-making efficiency and simultaneously create accurate information for decision-making effectiveness. According to the bounded rationality theory, the NPD decision-makers information evaluation tasks always include incomplete information that should be reduced to improve decision-making performances. When searching for a possible solution, what can be concluded from our exploratory case study at manufacturing firms for using AI information in their NPD decision-making?

The investigated firms incorporated two types of AI use in their NPD decision-making. First, “in-machine AI,” which is an addition to the machine and interprets performance data derived from sensors, uses deep learning to learn from these data, and uses what it learns to generate real-time performance information about customer circumstances. Second, “AI analytics,” which interprets online customer data sources, uses deep learning to learn from these data, and uses what it learns to generate future customer preference information.

These two types of AI can change the four evaluation information tasks of NPD decision-makers in different ways.

We found for the first task of information generation, that both AI lead to similar changes with regard to new information sources for the NPD. While in-machine AI created new sources for real-time product performance information, AI analytics created new sources of future customer preference information for a new market.

Second, the NPD decision-maker continues with the second task: evaluating the information inputs. While both types of AI lead to changes, they have different decision-making effectiveness results. We found that the in-machine AI leads to customer complaints or preferred customer adaptations that are hard to interpret, which complicates the evaluations of these information inputs. Thus, there is an undesirable decrease in decision-making effectiveness. On the other hand, AI analytics makes it easier to interpret future customer preference information through evaluating extensive amounts of online future customer behavior, thereby increasing decision-making effectiveness.

Third, the NPD decision-maker continues with the third task: project criteria evaluations. The in-machine AI information is not suitable for changes in this task and does not affect the decision-making effectiveness. The use of AI analytics does change the project criteria evaluations through externalized prioritizations of customer-related project criteria, which positively affects the decision-making effectiveness.

Lastly, neither AI use alters the last task, decision-making, as we found no indications from interview informants nor academical literature that it can increase decision-making effectiveness.

The actual effect of AI use-related changes on decision-making effectiveness is conditional.

First, our results have shown that decision-making efficiency moderates the achieved decision-making effectiveness by AI-related changes in information evaluation tasks. Informants recalled similar experiences: increasing the decision-making effectiveness by AI use would require more NPD resources, leading to less decision-making efficiency.

Second, the AI use-related changes that influence decision-making effectiveness is moderated by the type of NPD evaluation gate. The AI analytics-related changes improve the decision-making effectiveness during the non-physical evaluation gates, while the in-machine AI use-related changes improve effectiveness at the physical- and post-development gates.

Third, AI analytics has an additional condition of customer orientation that could moderate decision-making effectiveness. The AI analytics-related changes were positively assessed for decision-making effectiveness when the decision-maker was orientated on future customers and negatively when oriented on customers.

To conclude, AI information can improve decision-making within the NPD for certain incorporations in the information evaluation tasks. Nevertheless, this improvement is conditional as it depends on the type of AI used, the acceptance of lower decision-making efficiency, the type of evaluation gate, and the NPD customer orientation.

Chapter 6 Discussion

This thesis has investigated through the analysis of explorative case studies within manufacturing firms how two types of AI use changed the information evaluation tasks and, under certain conditions, could improve NPD decision-making. This chapter contains theoretical implications, the research limitations, suggestions for further research, and management implications.

6.1 Theoretical implications

This section discusses the different theoretical contributions from the research results related to the bounded rationality theory, the NPD information paradox, information challenges during the NPD evaluation gates and NPD customer orientation.

6.1.1 Bounded rationality theory

This subsection discusses the AI-related changes for the information limitation principles of the bounded rationality theory of Simon (1979).

Both AI uses did lead to new information sources, function to tackle incomplete information, and retrieve more understanding for predefined NPD problems. Our research showed that AI offered a solution to retrieve new information to better understand performance problems or future customer preferences.

Both AI uses did lead to different information evaluation inputs, but generate possible alternative information differently, leading to other decision-maker's considerations. Our research showed that AI analytics changed the evaluations to more alternative information inputs from future customers based on extensive data sources leading to more including decision-maker's considerations. On the other hand, in-machine AI makes it adversely harder to evaluate alternatives from customer inputs on predefined data sources leading to restrictions of decision-makers to consider new customer information.

Only AI analytics use did lead to changes in project criteria evaluations, evaluate more complete alternatives, and lead to better predictions of consequences. Our research showed that AI analytics increased the completeness of evaluations of future customer alternatives by better predicting the consequences of their preferences for NPD project criteria. In-machine AI did not lead to changes. We assume that it cannot offer complete evaluations from a predefined data source, without possibilities of adaptation.

Both AI uses did not changed decision-making, cannot select NPD alternatives, and cannot determine maximisation and optimisation decision criteria. Our research showed that humans determine these decision criteria based on estimations and experience, of which AI is not capable.

6.1.2 NPD decision-making paradox

Our research results contribute to the decision-making performance debate to reduce decision-making errors (Dijksterhuis & Nordgren, 2006; Eling, Griffin, & Langerak, 2013). In some cases, AI use could be a viable solution to reduce decision-making errors by creating more decision-making effectiveness, under the condition that securing efficiency is not a primary goal for the decision-maker.

In-machine AI was primarily used in the NPD to achieve goals of optimising machine performances by creating a source of real-time performance information. The decision-making effectiveness increased due to better linking performance information to technical alternatives for machine performance improvements. However, Davenport & Ronanski (2018) noticed that black-box reasoning are problematic for decision-making to understand and interpret AI information. Our findings were similar. In-machine AI black-box reasoning decreased the effectiveness of the same optimisation goals as new customer complaints and needs were not evaluable. Guszcza, Lewis & Evans (2017) confirms our findings stating that AI is inadequate for dealing with novelties. To conclude, it is debatable to what extend in-machine AI does lead to decision-making effectiveness. We suggest that this is contingent on the information challenge and the influence of varying customer information within the NPD.

AI analytics use focused on NPD goals for achieving a customer needs fit for a new market by creating better future customer preference information. For achieving customer needs fit goals, decision-making effectiveness increased due to a new information source, more accurate future customer preference evaluations, and externalized prioritizations of customer criteria. We found in line with Jarrahi (2018) that humans still need to decide which data to generate, and the AI can evaluate these data, which implies a risky situation. Busenitz & Barney (1997) emphasized the importance of dealing with uncertain events for NPD decision-making. So, AI analytics seems to only lead to improved decision-making effectiveness for risky situations and not uncertain ones. We found that AI analytics was used for increasing decision-making effectiveness of evaluating high varying customer behaviour information inputs, which rejects the statements of Martinko (1996) that high varying data always require intuition. Further, we found that AI analytics led to more effectiveness in prioritizing customer criteria for a new NPD project due to external evaluations of extensive online customer behaviour data. The NPD literature offers a possible explanation, noting that NPD project criteria evaluations would require rich information (Dijksterhuis, 2006; Eling et al., 2013).

The use of AI still leads to the previous mentioned information paradox for decision-makers, in which the use of AI could increase decision-making effectiveness if allocated with high resources to achieve that. Thus, it would decrease decision-making efficiency. This finding confirms the statements of Dewangan & Godse (2014) that decision-making efficiency is a moderator of decision-making effectiveness. We saw that informants had different opinions about AI use to reduce decision-making errors in their NPD. Mechanici's case study showed that if the expected increase in decision-making effectiveness was sufficient, the costs in decision-making efficiency were accepted, leading to investment for in-house AI development. However, CyclingXL's case study showed that if high-efficiency costs were expected, the increase in decision-making effectiveness was not justified, which lead to no investments for in-house AI development. Our research results made us assume that first informants must see a substantial decision-making effectiveness improvement for considering AI use on information challenges, and afterwards make a second consideration for decision-making efficiency.

6.1.3 Information challenges within the NPD

In our results section, we saw that the AI uses had various effects on decision-making effectiveness depending on the evaluation gates.

AI analytics increases the decision-making effectiveness more for non-physical NPD gates than for physical NPD gates. We assume that this is caused by the capabilities of AI analytics to analyse extensive amounts of information from different sources, handling the information intensiveness better during these phases. This assumption grounds on two theoretical explanations. First, during non-physical NPD evaluation gates decision-makers unmanageable amounts of ambiguous and complex information (Jespersen, 2012). One possible explanation for decision-making effectiveness is that AI analytics better resolve these information intensity challenges for NPD decision-makers. Second, decision-makers tend to use familiar sources and activities (Henderson and Clarke, 1990) leading to subsets of information with higher risks to fall into decision-making traps (Ahuja and Lampert, 2001). A second possible explanation is that AI analytics decrease the decision-maker's reliance on subsets of information, as it uses different and new information sources, thus, avoiding possible decision-making traps.

More decision-making effectiveness due to the use of in-machine AI for the development and post-development gates could result in more accurate real-time performance information. We assume that this decision-making effectiveness is achieved due to in-machine AI offer more real-time insights of machine performances for real-world circumstances so that they can adapt the latter NPD gates towards these insights. We did not find a plausible theoretical explanation for more decision-making effectiveness. Possibly it resolves information challenges mentioned by Bhuivan (2011) to meet real-time customer needs for adapting the development of machine performances towards during the physical gates. However, this explanation is somehow in contradiction with another finding, that in-machine AI decreased the effectiveness in meeting real-time needs for non-physical gates due to the lack of adaptation possibilities to new customer wishes. Our case studies of in-machine AI primarily focus on physical development gate experiences, thus might explain the findings for decision-making effectiveness of in-machine AI. Nevertheless, the actual experiences of in-machine AI use for more decision-making effectiveness during the whole NPD remain unclear.

6.1.4 NPD Customer orientation

Additionally, based on our inductive data analyses, we identified the role of the customer, or future market orientation of NPD decision-makers, to moderate decision-making effectiveness. AI analytics are based on unknown online information sources, which means that they do not accurately reflect current customer preferences. When focussed on current customers' aims, AI analytics does decrease the effective understanding and satisfaction of the current customer. However, this could decrease the NPD innovativeness (Christensen, 1997). On the other hand, AI analytics increase the decision-making effectiveness when focussed on the future market, because of the analyses on new information sources that contain the emerging needs and market development of potential customers. This future market orientation could increase NPD decision-making effectiveness (Hillebrand et al., 2011; Narver et al., 2004). Increases in decision-making effectiveness by AI analytics is theoretical explainable as it contains data-driven leadership and environmental scanning of information mentioned by Duan et al (2020).

6.2 Limitations and Further Research

In this section, we will discuss four main limitations of this research. First, this research aimed to explore the AI use-related changes of information evaluations for decision-making, which limited the pool of suitable Dutch NPD firms. The rareness of AI use for NPD decision-making with manufacturing firms further narrowed the selection of suitable cases. Two challenges were faced regarding the cooperation of informants as potential research cases: the rarity of AI use and the restrained participation of informants due to the critical strategic importance of firms. Consequently, this research gained limited access to research data, which led to merely four NPD firms that have been studied, combined with two additional AI supplier studies. This sample is too small to draw convincing generalisable conclusions. Nonetheless, this research provides guidelines for further research to create more focus on establishing the relationships between AI use and NPD decision-making. As the availability of research firms is limited, future research could adopt an experimental design with defined NPD conditions to provide more generalisable results despite the scarcity of AI use.

A second limitation is the number of informants and the burden of proof they provided. This research is based on three NPD informants with direct AI use experience, two NPD informants that offered expectations of AI use, and three AI supplier informants with secondary proof of AI use experiences of customers. Consequentially, the informants offered a different burden of proof towards AI use and NPD decision-making. Due to the limitations in resources, this purposive informant selection was chosen as it offered more explorative insights into the new phenomenon. However, it restricted the generalizability of the NPD decision-makers population. Future research could expand the amounts of NPD informants, number of cases, or apply more varied organisational contexts for more convincing and reliable results towards AI use and decision-making.

The third limitation is the broad exploration of a wide range of AI technologies and NPD evaluation gates. This limitation occurred for two reasons: the researcher lacked detailed knowledge of AI techniques, and decision-making literature offered insufficient insights or arguments to base choices towards a specific evaluation gate on. Consequently, the study was not capable of traversing the specific evaluation stage and AI information in detail. Desk research on the information gaps was not entailed due to failures to achieve permissions of company documents. Therefore, this study cannot encompass the entire range of information challenges related to AI and is limited to essential information challenges within the NPD. This research did offer explorative suggestions for further specifications. Future research could specify AI analytics towards the non-physical evaluation gates and in-machine AI to subsequentially evaluate gates to create more detailed insights into the AI use-related changes and the effects on decision-making effectiveness.

A fourth limitation relate to the role of the researcher. The semi-structured question list for NPD informants was based on theoretical insights, however appeared not a logical question structure during the interviews. That resulted in non-sequential answering of informants to the interview topics, which led to missing answers and complications in analysing the predefined concepts. The choice not to use a specified AI definition for strengthening exploratory insights, in the meantime complicated the clearness of the AI definition for the informants. While the AI research definition was mentioned during the interviews, we found indications during the analyses that informants might misinterpreted the AI definition and used their own AI definition for answering. Therefore, it is recommended for future research to start the interview with defining AI and use a more specified AI definition for informants.

Based on our theoretical discussion, we found two additional paths for future research. First, we found that through inductive data analyses, the type of NPD customer orientation seemed to relate to decision-making effectiveness. However, we did not focus on this aspect in this study. Future research could be conducted to explore if AI analytics use can offer support in strengthening the future market orientation of NPD decision-makers. Second, we found that in-house developed AI use demanded high NPD resource costs. However, third-party AI analytics does not require development, and could, therefore, change the information trade-off. Future research could solely focus on the use of third-party AI analytics for NPD decision-making towards the information paradox.

6.3 Managerial implications

The research findings imply notable implications for NPD decision-makers to guide them in improving NPD decision-making by AI use.

The first action of the NPD decision-maker is to identify the NPD information challenges and consider the necessary information for improvements. This identification is essential because the two AI uses deliver different information advantages. In-machine AI use provides real-time information that offers insights into performance conditions of the machine in real-world circumstances and fits the physical- and post-development evaluation gates. AI analytics use provides more extensive analyses of future customer behaviour from online sources to better understand potential needs for the NPD. Thus, it fits the non-physical development evaluation gates.

Afterwards, the NPD decision-maker should choose how to proceed with limited information and how to minimise decision-making errors. The use of AI information demands consideration for the information trade-off between decision-making effectiveness and efficiency. The NPD decision-maker should bear in mind that eventually reducing decision-making errors through AI use requires high resource costs to create accurate AI outputs, thus, accepting less decision-making efficiency. If the decision-maker does not want to give up decision-making efficiency, exploring third-party partners that offer AI analytics inputs from relevant customer sources to improve decision-making effectiveness could be the results.

Carefully considering the information trade-off should not be underestimated before considering any incorporation within the decision-making process. Both AI lead to different changes and have different guidelines to consider by NPD decision-makers.

When considering in-machine AI, new real-time performance information seems the central advantage of NPD decision-making. The decision-maker should consider this a substantial advantage for its NPD, because of the ensuing disadvantages. The in-machine AI outputs do not offer motivations for its identified problems, potentially leading to less understanding of the machine development when trying to solve customer complaints or making new adaptations. Furthermore, the in-machine AI outputs are not likely to offer substantial changes in project criteria weights or decision-making automatization because AI outputs lack interpretation possibilities for NPD decision-makers.

AI analytics could offer a new online customer behaviour source to generate a new understanding of potential needs for the NPD. When the decision-maker orients its NPD towards current customer aims, AI analytics might not offer suitable customer preferences as it provides future market information. If aiming for future market NPD orientation, AI analytics could evaluate future customer wishes from online sources to create more understanding for needs related to the NPD. Whereas AI analytics could offer a better alternative for manual evaluations by external weightings for product project criteria evaluations, decision-makers should be alert that AI analytics only evaluate one project criteria group and not weight all project criteria simultaneously. Thus, it is not capable of automating any decision-making.

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Appendices

Appendices will not be provided for this public version.