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The Opportunities and Challenges of Artificial Intelligence in New Product Development

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ABSTRACT:
The importance of artificial intelligence (AI) has developed rapidly through various industries, however, one key area where its role is still facing high uncertainty in adoption is new product development (NPD). It is currently not applied evenly across the NPD process stages; the results of this thesis indicate that particularly mid- to late NPD stages have seen most AI adaptation as of now. Yet, stages where applications are still lacking especially are early stages of NPD such as ideation and go/no-go decisions. This thesis aims to present a comprehensive overview of the challenges associated with AI adoption in NPD, the opportunities it could enable, the areas where is has been utilized so far as well as it’s anticipated role in the future of NPD.

This thesis is conducted as a systematic literature review, where thematic- and comparative analysis methods are applied to structure recurring themes into key findings and comparing significant findings with established theoretical frameworks. The theoretical framework of this thesis is carried out with three theories that deal with lifecycle of innovative change: Diffusions of Innovations theory (DOI), Dynamic Capabilities theory (DCT) as well as Disruptive Innovation theory. The literature analysis of this thesis reviews various peer-reviewed academic JUFO rated articles, complemented with book-based case examples and classic literature around the topic.

Furthermore, DCT indicates that well-directed “sensing” assessments along with “seizing” and “reconfiguring” mechanisms could enable organizations to transform risks and uncertainties into value adding resources instead. According to DOI, relative advantage, compatibility and complexity are some of the key concepts that can be used to interpret organization’s cost-benefit ratio to explain its classification as an adopter of a new technology. Disruptive Innovation theory indicates that AI in NPD can be categorized currently as a “sustaining” technology because it was considered to be value adding across all the examined case examples.

This study contributes to the existing literature by compiling a study that utilizes DOI, DCT and Disruptive Innovation theory in the context of AI in NPD. The results of this thesis provide useful insights for organizations looking to consider AI adoption in some of their NPD process stages. This thesis also points out research gaps and directions for future research of the topic, as such it also contributes to valuable knowledge to the researchers around the topic.

KEYWORDS: artificial intelligence, new product development, innovation, uncertainty, organizations, technology adoption

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TIIVISTELMÄ:

Tekoälyn merkitys on kehittynyt nopeasti useilla eri toimialoilla, mutta yksi keskeinen osa-alue, jossa sen rooli kohtaa edelleen runsaasti epävarmuutta käyttöönotossa on uusien tuotteiden kehitys. Tällä hetkellä sitä ei sovelleta tasaisesti kaikilla uuden tuotekehityksen prosessin vaiheissa ja tämän tutkimuksen tulokset osoittavat, että sitä on sovellettu eniten uuden tuotekehitys prosessin keski- ja loppuvaiheissa. Vaiheet, joissa sovellutuksia on vähemmän, ovat erityisesti prosessin alkuvaiheet kuten ideointi ja hyväksymys/hylkäämispäätökset. Tämän tutkielman tavoitteena on esittää kattavasti sen käyttöönottoon liittyvät haasteet, mahdollisuudet, osa-alueet, joissa sitä on tähän mennessä hyödynnetty sekä sen arvioitu rooli tulevaisuuden näkökulmasta.

Tutkielma toteutetaan systemaattisena kirjallisuuskatsauksena hyödyntäen temaattista- ja vertailevaa analyysimenetelmää jäsentäen toistuvia teemoja kirjallisuuden ympäriltä keskeisiksi havainnoiksi sekä vertailemalla merkittäviä havaintoja teoreettisten tulkintamallien avulla. Teoreettinen viitekehitys toteutetaan kolmen innovatiivisen muutoksen elinkaarta käsittelevän teorian avulla, joita ovat Diffusion of Innovations -teoria, Dynamic Capabilities -teoria sekä Disruptive Innovation -teoria. Tutkielman kirjallisuusanalyysissä tarkastellaan vertaisarvioituja JUFO-luokiteltuja akateemisia artikkeleita, joita täydennetään kirjoihin perustuvilla tapausesimerkeillä sekä aihetta käsittelevällä alan klassikkokirjallisuudella.

Dynamic Capabilities -teoria osoittaa, että oikein suunnatut tunnistamis-, tarttumis- ja uudelleenkonfigurointikyvykkyydet mahdollistavat riskien ja epävarmuustekijöiden muuntamisen arvoa lisääviksi resursseiksi. Diffusion of Innovations -teoria puolestaan kertoo, että suhteellinen etu, yhteensopivuus sekä monimutkaisuus ovat esimerkkejä keskeisistä käsitteistä, joiden avulla voidaan tulkita organisaation kustannushyötysuhdetta selittäessä sen luokittelua uuden teknologian omaksujana. Disruptive Innovation -teorian mukaan tekoäly voidaan luokitella tällä hetkellä ”ylläpitävänä” teknologiana uuden tuotekehityksen saralla, koska sitä pidettiin lisäarvoa tuovana kaikissa tarkastelluissa tapausesimerkeissä.

Tutkielma täydentää olemassa olevaa kirjallisuutta aiheen ympäriltä kokoamalla tutkimuksen, joka hyödyntää näitä kolmea teoriaa osana tekoälyn tutkimusta uuden tuotekehityksen saralla. Tutkielman tutkimustulokset tarjoavat hyödyllisiä näkemyksiä organisaatioille, jotka harkitsevat tekoälyn käyttöönottoa joissakin uuden tuotekehityksen prosessin vaiheissa. Tutkimus tuottaa arvokasta tietoa aiheen tutkijoille nostamalla esiin tutkimusaukkoja sekä ehdottamalla suuntauksia jatkotutkimukselle.

AVAINSANAT: artificial intelligence, new product development, innovation, uncertainty, organizations, technology adoption

Contents

1 Introduction

The general concept of product development (PD) process can be explained with six phases – the phases are the following, planning, concept development, system-level design, detail design, testing and refinement as well as production ramp up (Ulrich et al., 2019, p. 14). New product development (NPD) can be seen as process consisting of series of gates, also leading to term “stage-gate process” (Cooper, 2024, p. 63). Regarding the topic, a definition of AI within the topic can be viewed as information process of NPD process from idea to launch of the product (Cooper, 2024, p. 63). Furthermore, Cooper also points out that new product process is just all about the tasks designed to gather information for the purpose of reducing uncertainty and therefore being able to manage the risk better. The actual definition of artificial intelligence (AI) is the following, the ability of computers or other machines to be able to exhibit or simulate intelligent behavior (Oxford English Dictionary, n.d.).

With these definitions the basic idea of this subject can be understood which is “The Opportunities and Challenges of Artificial Intelligence (AI) in New Product Development (NPD)”. However, a single universally agreed definition to NPD doesn’t exist so there is a certain freedom to it. In fact, many academic articles have varying definitions of NPD and thus many organizations, companies and individuals have their own definition to fit their own needs.

AI is one of the fastest emerging and potentially most revolutionizing technologies now. It can impact many operations across different industries; one of the key operations examined in this thesis is NPD, where AI could greatly enhance innovation and improve decision-making through the whole product lifecycle. The importance of this research can be found by exploring the opportunities and challenges for valuable insights for businesses, organizations, companies and product developers that want to leverage AI in their functions.

Overall, AI is becoming the new catalyst for smarter, faster and more efficient product innovation and you don’t want to be the one to miss the train.

1.1 Background of the Study

The global interest towards AI has risen across many functions and areas across different organizations. One source by McKinsey & Company has suggested together with the value creation aspects, it can also revolutionize internal knowledge management systems across organizations (McKinsey & Company, 2023, p. 13). They also connect the potential to product research and development where they will suggest that enhanced design, improved product testing and quality along with ideation could be transformed with the help of AI (McKinsey & Company, 2023, pp. 22-23). These factors are connected to the stage-gate model of NPD which will be introduced in greater detail in some of the upcoming chapters. However, despite the swift proliferation of AI interest, many studies seem to point out that AI implementation across NPD is facing challenges in adoption.

In one of Cooper’s articles, he talks about the substantial payoffs that AI could reap in NPD, mentioning that the number one benefit is increased innovation (Jyoti & Riley, 2022, as cited in Cooper, 2024, p. 62). He also makes a case for the implications as to why AI is facing challenges in adoption, uncertainties and unknowns exist such as lack of a strong business case, adoption perceived as costly, lack of right mindset as well as risk and ethical issues (Cooper, 2024, p. 62). The study by Cooper titled as “The AI transformation of product innovation” was one of the first studies that was stumbled across while researching the state of AI adoption in product development. It was of inspiration to explore the topic more in depth thus it was found out that many studies have examined this topic from a broader perspective or from different unrelated angles. The missing link for what required answers for specifically in NPD was that in which ways have AI been applied in NPD processes in practice, what role is it implied to take, where does it stand currently, can perceived challenges and opportunities be rationalized with theoretical frameworks and how transformative its reach could be across organizational functions.

1.2 Objectives of the Study

The objective of this thesis is to explore the current and upcoming state of AI in NPD. By compiling theories with vastly different frameworks and approaches some of the most notable, pivotal and influential studies from recent years as well as some of the defining core literature will be aligned with the research goals. As the goal of this thesis is to review the state of AI in NPD, this will naturally lead us towards research goals that inspect the fundamental qualities, premises, implications, uncertainties, attitudes and projections of its adaptation as a new technology. The research questions were chosen to acquire some of the most meaningful results and findings to cover all these areas.

The first research question goes as follows: In which areas of New Product Development have Artificial Intelligence been used and what kinds of opportunities does its use offer? This research question is going to reveal some of the current attitudes and predictions towards the future of AI in NPD in a prospective and promising light. Whereas it will also shed light on basic understanding of what has been done so far in this domain.

The second research question was chosen because it was reasoned to highlight some of the perceived constraints and barriers that could be impeding or hindering the current and upcoming applications and adaptations of AI in NPD. This research questions goes as follows: What are the main challenges in introducing Artificial Intelligence in New Product Development?

Third research question is the following: How does literature evaluate the role of Artificial Intelligence in New Product Development now and in the future? The last research question will cover the theoretical stances of some of the key literature and studies done on this topic. This will provide us with credible and critical knowledge of the questioning approach towards the subject of study.

1.3 Research Methodology and Limitations

Literature review was chosen as the overall basis for this thesis. Essentially it came down to weighing the opportunity cost between doing a literature review versus an empirical study. As for the study, the purpose is to evaluate the opportunities, challenges, research gaps, the prospects and current standing of AI in NPD. To best advance towards these research goals, it was important to choose the most streamline and comprehensive method for advancing. This research's purpose is to evaluate the research questions on a theoretical and strategic level instead of technical and detailed manners. Thus, this study is aiming to get a more comprehensive and broad perspective towards the topic which pushes the objective more towards the literature-based perspective, synthesizing existing knowledge into analysis without the need to produce new data from e.g. surveys or interviews.

The literature review will follow a systematic research design, ending up with this decision coming down to convenience and the nature of the research subject. The subject area is in a rapidly emerging and evolving field, so it will be important to contextualize and synthesize the answers to the research questions in the most critical, reliable and transparent way. Given the fact that the research done on this field is fairly new, it will be beneficial to assess the sources in a structured manner. What excluded other potential literature review approaches was highly related to the overall aim of the research. The goal is to produce unbiased, relevant and comprehensive overview of the challenges and opportunities that arise from the introduction of AI within NPD.

One feasible alternative option would have been scoping review style design, which could provide a broad overview of the topic and analysis of what is known and unknown on the subject. However, the aim of scoping review style literature review is to focus on finding research gaps by mapping key findings on the research subject (Tieteen termipankki, Kartoittava katsaus, n.d.). This would lead to more open-ended research with less in-depth analysis, which ultimately is the reason why this research design was excluded.

Yet another research design would be an integrative review, which is explained as follows: "an integrative review is a specific review method that summarizes past empirical or theoretical literature to provide a more comprehensive understanding of a particular phenomenon or healthcare problem" (Broome, 1993, as cited in Whittemore & Knafl, 2005, p. 546). However, in case of this thesis it was not convenient to gather empirical data to explain specific phenomenon, thus this study leaned towards other research designs.
Perhaps the less relevant research design could have been narrative style design, which implies that sources are chosen based on the desired results that the researcher might seek. In this research design style, the outcomes are also highly influenced by the decisions made by the author (Tieteen termipankki, narratiivinen katsaus, n.d.). In this case the thesis was aiming for more systematic and thorough research, so this method was left out of the question.

Since it has now been reasoned to be a literature review based systematic research approach. Next up, the data analysis methods for the research must be justified. The possible data analysis methods could be the following for example: thematic analysis, comparative analysis, content analysis, narrative analysis or discourse analysis. It is quite the critical decision to choose optimal data analysis methods as these will play a huge role in shaping what results, findings and conclusions will be made at the end. Since this research will focus mainly on theoretical and text-based sources, it is a fitting decision to choose qualitative analysis methods such as these.

Let's go over each method that didn't make it to the study and why that is.
Discourse analysis is described as a process to research publications from the viewpoint of a communicative process, which looks at social norms, settings-, and structures for perspectives (Dant, 1991, as cited in Wall et al., 2015, p. 260).
Narrative analysis for instance is defined to focus on personal stories of individuals coming from their personal experiences, best usage case being mentioned as narratives or stories to do an analysis on (McLeod, 2024, pp. 1-2). This approach doesn't fit right

with the research goals of this thesis as this study is not looking to analyze events, stories, experiences or narratives. The goal is to analyze opportunities and challenges of AI within NPD in systematic way to find patterns, trends and observations that way, so for this reason it was decided on another research method.

As for content analysis, the following factors have been concluded. “It is a method aimed to interpret and identify information from recorded forms of communication and that its particularly useful in scenarios which include vast amount of unanalyzed textual data” (Kleinheksel et al., 2020, p. 127).

It is also further described that the most common methods of common and effective types of content analysis can be made from transcribed content or text such as open-ended survey responses or interviews.

For this thesis’ purposes identifying common themes and key points across literature would be more relevant and fit for the emerging nature of the field of AI within NPD. Content analysis was not chosen because the thesis’ goals are not to analyze individual documents or transcribed content, instead the goal is to analyze broader perspectives among the subject.

The data analysis methods that were chosen at the end were thematic- and comparative analysis methods. Thematic analysis method is mentioned to revolve around identifying patterns and reporting patterns in a data set based on qualitative data for the purpose of interpreting them through these patterns (Naeem et al., 2023). This is a very fitting constructed and systematic approach to the study; the reason this method was chosen was because the key to identifying the challenges and opportunities of AI in NPD will be to find key themes among the sources and studies, this method will back up the research with strong evidence, trends and concepts.

Comparative analysis is another method that was chosen for this research. As explained by Esser and Vliegenthart, “comparative analysis guides us our attention to the explanatory relevance of the contextual environment for communication outcomes and aims to understand systematic context shapes” (Esser & Vliegenthart, 2017, p. 3).

It is also said in their article that factors of influence explain different outcomes regarding what the subject of investigation is. Ultimately, this method was chosen because it will help to contextualize differences and similarities between the studies, identify contextual key points and ensure that deep understanding will be acquired of AI in NPD.

Now it would be a good time to explain the data collection methods and sampling strategies. The following key words are the most important in my research, AI, NPD, challenges, opportunities and innovation. With these keywords such search phrases can be structured that will result in finding relevant sources for this study. In this systematic literature review-based research the study is aiming to analyze secondary data from different academic databases. The following data bases for example, were used to gather data from ScienceDirect, Academic Search Elite, Emerald Journals, IEEE Xplore and Google Scholar. The search phrases were constructed to find sources with different perspectives and focuses but still using some of the keywords to end up with relevant results.

Some examples of the search phrases that were used are the following, “Artificial Intelligence” AND “New Product Development”, “Artificial Intelligence” AND “New Product Development” AND “Future”, “AI adoption” AND “New Product Development” AND “Challenges”, “Artificial Intelligence” AND “New Product Development” AND “Innovation”, “AI” AND “Innovation” AND “Product Development”, “AI-driven innovation” AND “Product Development” along with "Artificial Intelligence" AND "innovation" AND "R&D" AND "Product Development" OR "New Product Development"

The sampling strategy is structured in a convenience-based criteria. The sources must be ranked at least JUFO 1 but preferably at least JUFO 2. JUFO 1 ranked sources were chosen if they were specifically relevant and had strong academic characteristics in them. The inclusion criteria followed mainly studies that were published during the last 5 years, exceptions we made if the studies focused more on theoretical foundations or frameworks and were considered classic literature e.g. books as sources. Another factor was that the sources had to be peer-reviewed articles.

Exclusion criteria excluded studies that had insufficient evidence of academic foundations. Studies that were in other languages other than English were not included into the research. Lastly, studies that were done in too narrow fields of study that didn't add exceptional value to the study were left out.

Database	Keywords used to search literature	Number of articles found (initial search)	Number of relevant articles	Number of finally selected articles for review
ScienceDirect	Artificial intelligence, innovation, new product development	~ 900	~ 40	3
Academic Search Elite	AI, NPD stages, organizations	45	7	1
Emerald Journals	Gen AI, innovation, opportunities, challenges	~ 40	~ 10	1
IEEE Xplore	NPD process, AI, product innovation	5	5	3
Google Scholar	Product development, AI, opportunities, challenges, market analysis	Numerous	~ 20	2

Table 1

Table 1 presents the literature search process for the literature analysis section of this thesis. Five data bases were primarily used to look for peer-reviewed academic articles that each had something new to add to this thesis. Some of the articles were examined more in depth for their thorough approach for addressing AI in NPD with the focus on organizations or innovation. Few of them were used as a supplementary source to support the primary sources.

The initial search for articles often resulted in broad range of relevant to highly irrelevant set of articles. Out of the initial set of articles found, many of them were screened based on abstract, titles and relevancy to the topic. The articles that made it into the literature review were just 10 of the most relevant peer-reviewed JUFO rated articles that each had some purpose or otherwise contributed in some way to the literature analysis.

On top of that, academic core literature was also present through the literature review section of this thesis. Specifically, one book was analysed more thoroughly because of the practical case examples it presented of AI adoptions in organizations. That book in question was Artificial Intelligence in Practise by Marr & Ward. At the end of this thesis, the reviewed articles are listed in Appendix 1 according to themes.

Ethical considerations on the research were maintained with academic integrity, meaning that since this study focuses on secondary data sources such as academic articles and literature, the main concern was plagiarism and citations. The study will follow writing guidelines of University of Vaasa; thus APA 7-style citations were used according to the guidelines. For the avoidance of plagiarism, careful and exact references and citations were made to attribute for the text of the original authors. Confidentiality was addressed by avoiding sensitive or confidential information in the study, the ethical guidelines of the original authors were respected and practiced during the study.

2 Introduction to Artificial Intelligence in New Product Development

“Prediction is at the heart of making decisions under uncertainty, which is a major part of new-product project, hence the transformative role of AI in NPD” (Cooper, 2024, p. 63). This quote illustrates the position of AI implementation in NPD perfectly well, as it might also be in many other fields or numerous other technologies as well. The reason this quote resonates with this topic is in the way literature assesses AI’s stance in NPD processes as highly varying, comprehensive and multi-faceted as are the stances settled towards challenges and opportunities associated with.

Some of the recurring themes that have been identified are knowledge-based interpretations, where the perceived value gain is one of the key principles what organizations consider. Risk management or risk assessment types of approaches are often presented where organizational decisions or attitudes are often compared in line with the willingness to adapt and delve into the unknown. Then there are the efficiency perspectives where operational tasks especially are considered for AI to have a potential to take over, these in literature are explained as the idea generation phase and concept testing (Cooper, 2024, p. 64). Often considered is also the data quality and quantity related handling, usage, reliability and safety related factors when it comes to AI generated data especially. Creativity based approach and value proposition are often presented in the studies from idea generation point of view all the way to commercialization activities, actually one of the most studied and discussed themes regarding this.

The reason why AI implementation might be considered in NPD processes in an organization is that they might gain some of the following benefits according to a study. AI usage in NPD can offer new opportunities for better development of product ideas, improved business analysis capabilities, more innovation in product design, quicker commercialization and better quality of post-commercialization services and also more efficiency in operations management (Kakatkar et al., 2020, as cited in H. Zhang et al., 2021, p. 50).

2.1 Theoretical Foundations

The core theories present, that work as a theoretical backbone to this thesis are the following three theories: Diffusion of Innovations Theory (DOI), Dynamic Capabilities Theory (DCT) and Disruptive Innovation theory. With these three theories, the research questions will be answered systemically by developing the research questions in line with the theories presented. The connection, links and applications will be discussed as well as research gaps that might arise from the analysis.

AI, PD and NPD being already explained in introduction chapter, the remaining concepts that still deserve an overview are opportunities and challenges. What are the opportunities and challenges aiming to overview in this context when we are examining the effects of AI in NPD processes?

In an excellent scientific article on the topic by Robert G. Cooper. The author explains that with the help of AI, the following things can be enhanced in NPD, which are idea generation, testing of product concepts, improved Go-to-Development investment decisions, acceleration of product creation – physical development and testing of it (Cooper, 2024, p. 64). Another 5 benefits that are also mentioned there are the overall advancement of innovation, meeting customers' needs better with improved product design decisions, more efficient and faster time-to-market in products from datasets to prototyping to eventually design decisions, cost savings by removing human resources from tasks such as data analysis and testing phases and lastly the overall improved product quality because of customer feedback analysis being improved (Cooper, 2024, p. 69).

Some of the challenges that are discussed and considered in the same article include factors such as risks which are mentioned to be the following. Inaccuracy of the results, cybersecurity related risks, protection of intellectual property, regulatory compliance, ethical concerns (Cooper, 2024, p. 70). While the article mentions that these risks are commonly reported by about half of the firms mentioning the first four ones that were listed, it focuses on giving solutions to the risks rather than analyzing them thoroughly. Let’s disperse the studies and look at an academic article by Aron Witkowski and Andrzej Wodecki. For their article they have conducted an interview from IT-sector organizations from Poland. The following challenges were brought up as challenges when implementing AI to PD and management processes. The high volume of quality data that requires processing for improved business decisions, expectations of what can be achieved by AI – and the approach of people within the organization towards AI solutions, security concerns and privacy related to the data when external companies are connected to the tools and the process, trust and explainability of the formed data to be presented to the product manager, computing power required to maintain and implement the AI solutions and lastly mentioned factor being lack of clear methodology in introducing AI to PD and management processes (Witkowski & Wodecki, 2024, p. 145).

The Diffusion of Innovations theory consists of the process of diffusion and the concept of innovation (Rogers, 2003, pp. 11-12). Rogers has explained in his book that diffusion would be the process in which “an innovation is communicated through certain channels over time among the members of a social system”. Innovation he sees as “an idea, practice or object that is perceived as new by an individual or other unit of adoption”. He also connects the so-called innovation-decision process to the theory. In this process the individual or other decision-making unit goes from initial heaps of knowledge of innovation to form an attitude towards innovation and decision of continual of the innovation. If the decision is passed on further in this process, then the idea will transform into a new idea and confirmation of the decision (Rogers, 2003, p. 168). A stage model is also presented in the book, in which communication channels follow a model in the information-decision process; first it starts with knowledge, then it passes on the persuasion stage, after which comes the decision phase followed by the actual implementation stage to which lastly is added the confirmation stage (Rogers, 2003, p. 170).

Connected also to this theory would be the rate of adoption. In the book rate of adoption is explained by “the relative speed with which an innovation is adopted by members of a social system (Rogers, 2003, p. 221). There he also explains that this adoption can also be measured in numerical indicators of the adoption curve of those who adopt an innovation.

Next thing that should be brought up related to this theory would be the adopter categories. The following ones apply, innovators “venturesome”, early adopters’ “respects”, early majority “deliberate”, late majority “skeptical” and laggards “traditional”. These traits fit in line with the descriptions quite well. Innovators characteristics include interest in new ideas and strong tendencies to be willing to accept uncertainty. Early adopters are described more as “localites”, opinion leadership is also a factor for this category. Early majority refers to the adopters of an idea just before the average person, individual, organization or so forth. Late majority then naturally is the adopter just after the average person, individual, organization or so forth. Laggards are the very last group to adapt to new innovations, described also as near isolates in social networks of their system. The adopter categories were also described in Roger’s book. (Rogers, 2003, p. 284).

The Diffusion of Innovations theory can be especially helpful while analyzing the challenges of adopting AI to NPD. As the theory presents many characteristics and factors that might affect the adopter categories, theoretical links and applications might be applied to the scenarios and studies in the analysis. With the theoretical framework of this theory, the opportunities might also be recognized better to fit to each adopter group. The characteristics of diffusion and the ideas of innovation process can be looked upon by several characteristics and attitudes found by the studies, together with other theories the big picture can be recognized and built systematically.

The Disruptive Innovation Theory focuses on the reasons, premises and implications of what approaches and principles cause firms to fail with the adaptation of new technologies. The fundamental comparison is between sustainable and disruptive technologies. Christensen in his book explains that the basic principles of sustaining technologies is that they are in some way capable of improving the performance of established products, along with customers in major markets historically considering to be of value (Christensen, 1997, p. xv). The main principles of disruptive technologies are that they are resulting in worsened product performance, they are generally considered to be underperforming established products in the mainstream markets (Christensen, p. xv, 1997). Another characteristic that he lists there is that these disruptive innovations bring a vastly different value proposition to the markets, these products based on such technologies are usually cheaper, simpler, smaller or more convenient to use (Christensen, 1997, p. xv).

Upon this theory, it is also presented a third concept for which they call the "value network". In value networks companies' ought "to identify and respond to customers' needs, solve problems, procures input, reacts to competitors and aims for profit" (Christensen, 1997, p. 32). One key element to value networks is that company's historical market behaviors and choices affect the perceived economic value and potential of the new technology (Christensen, 1997, p. 32).

According to Christensen the so-called technology S-curves are a core part of the value networks. The basic proposition of the theory is that when technology is at different stages in its lifespan, then the engineering efforts connected to the product's improved performance are going to differ (Christensen, 1997, p. 39). The link between technology S-curves and value networks is found in the point where old and new technologies intersect in such a way that it will be the right timing for firms to introduce the new technology to their strategy or processes (Christensen, 1997, p. 39).

The implications of managerial decisions and their connection with sustaining and disruptive technologies, according to Christensen, is that managerial decisions can be seen as a six-step process. First step that he conducted based on many interviews was that disruptive technologies often would be first developed within established firms by engineers, utilizing bootlegged resources (Christensen, 1997, p. 43). Second step, the marketing personnel seeks reactions from the most important customers. Third step, established firms themselves defines the pace in which sustaining technological development occurs. Fourth step, after new companies are formed then disruptive technologies are found by trial and error. Fifth step, the entrants in the technology are moving in an upmarket direction. Sixth step, the final step established companies joined in late to hold on to their customers (Christensen, 1997, pp. 42-47).

The Disruptive Innovation theory is a very valuable tool to complement the research goals for this bachelor's thesis. This theory can help recognize the root causes as to why companies might run into obstacles on their way to adapt AI in NPD processes. With the help of this theory, suggestions and possibilities might also be recognized from case examples and literature, as to what might be some alternative solutions or approaches to the matter.

Overall, this theory can create fundamental theoretical foundations to the core research questions and help recognize whether AI introduction in NPD processes is a sustaining or disruptive technological approach. The six-step process presented in managerial decisions can be looked upon in the analysis to find connections between the practical introduction that have been made by companies, their attitudes towards AI as a new emerging technology and whether they can be applied to this six-step process. Last but not least, value networks can be analyzed and examined from case examples and literature that study AI in NPD.

The final theory that is introduced as a part of the research is called Dynamic Capabilities Theory (DCT). The theory is presented as a theoretical framework that sees “dynamic capabilities as the foundations for enterprise level competitive advantage for rapid technological change” (Teece, 2009, pp. 46-47). The basic frameworks of the theory suggest that “the extent to which an enterprise deploys and develops “nonimitable” dynamic capabilities will determine the nature and amount of intangible assets it will create and/or assemble and the economic profits it can earn” (Teece, 2009, pp. 46-47). Extended explanation on the same section by Teece also mentions that the theory points out that while the past affects the current and upcoming aspects, still there is a lot that the management can still do to change the future by investment choices and other decisions.

The theory itself can be broken down into three parts. These parts as explained by Teece in chapter one, are the following. Part one is the so-called sensing of opportunities and threats in the competitive markets. He presents that enterprises should constantly “scan, search and explore opportunities in technologies and markets, mentioning that both “local” and “distant” opportunities should be sensed” (Teece, 2009, pp. 18-19). The second part of the theory is called “seizing”. Seizing opportunities is presented by the means of that the “sensed opportunity has to be through new products, processes and services (Teece, 2009, pp. 23-24)”. He explains that this phase most of the time requires investments in development and commercialization activities. The third part of the theory is the maintaining phase, in which competitiveness is maintained by “enhancing, combining, protecting and if necessary, reconfiguring the enterprises tangible and intangible assets” (Teece, 2009, pp. 14-15). Essentially, he explains that for profitable growth, these qualities will be required from the enterprise. “The enterprises’ ability to recombine and reconfigure assets and organizational structures as the enterprise grows, markets and technologies change” (Teece, 2009, pp. 36-38).

While DOI might be the best theory in relation to identifying, analyzing and recognizing the challenges of introducing AI into NPD. DCT on the other hand might be the most valuable theory when it comes to opportunities viewpoint. With the help of DCT as mentioned, non-imitable dynamic capabilities are seen as the driving force for successful adoption of new technology in the emerging competitive markets. The studies, case examples and literature of the field will be analyzed in comparison with the DCT perspectives. New ideas and viewpoints might be recognized better with their structured approach and toolset.

The different parts of the theory can be applied to any scenario in which new technology (AI in NPD in this case) is being implemented in an organization with the goal of competitive business goals. The different parts of the theory can be systematically applied to the studies. The sensing of opportunities and threats will be a valuable step for creating a solid basis for the project, without proper search for these factors other organizations will already have the edge. The seizing of sensed opportunities is crucial to be done in line with the value that the new product, service or process creates for the organization, if this is not the case, then the organization should ask themselves what the point was of implementing this technology with the goal of competitive advantage if any of it can't be seized. The third part of the theory focuses on the ways in which the organization can maintain its competitive advantage by being adaptable and on top of its game. If an organization is neglecting its obligations for ability to reconfigure, develop and further be ready for change, then they are not capable of maintaining profitable and competitive technological change according to the theory.

2.2 Literature Review: The Stage-Gate Model

The key studies that have investigated AI implementation in NPD shall be reviewed and compared in this chapter. Should it be stated that comparison is done at surface level in this chapter, as more in-depth applications of the thematic- and comparative data analysis methods are applied later in "Results & Findings" section. The purpose at this point is to review the core frameworks of the key topics that are recurring between the studies, make notes of the similarities and differences between the results of the studies and also to synthesize these studies in such a way that it will be convenient to further continue build “the bridge” towards “Results and Findings” from the insights from here.

The first recurring concept among the different studies is that often there is some definition of NPD process consisting of stages. The definition, meaning and number of stages can vary. As in perhaps the most commonly known definition by Robert G. Cooper, the so-called stage-gate model consists of five gates or six phases. The first gate being between ideation and concept, second gate between concept and building of business case, third gate between building of business case and development, fourth gate between development and testing and the fifth gate between testing and commercialization (Cooper, 2024, p. 65). Another presentation of the typical NPD process suggests that the first stage would be idea development, business analysis, product design, product testing, commercialization, post-commercialization and operations management (Zhang et al., 2021, p. 51). Yet another interpretation of the process that was found consists of nine different stages, in this model the first stage is idea generation, then idea screening, project proposal, project clarification, concept creation, prototype development & testing, product development, launch and post-launch review (Harmancioglu et al., 2007, p. 406). What can be summarized from these is that they all seem to follow the formula starting from somehow managing the initial idea, then varying steps from conceptualization to development to business case to testing to commercialization and in some models’ post-commercialization efforts or management. The structured and recurring themes between these models imply that the core framework is established and agreed upon.

2.3 Literature Review: Uncertainty

Often discussed theme among these studies is that of uncertainty. In different studies it is one of the most commonly brought up points currently being the most notable barrier or “roadblock” preventing AI from taking over NPD faster globally. In many of the articles I have reviewed, the premise is that uncertainty is being formed from lack of knowledge as to what value might be gained from the adoption of AI within the NPD processes.

More often than not firms are not convinced that AI adoption within their NPD processes can offer measurable value to their business. Management can be cautious because of the lack of broad research, thorough studies at large scale and overall proof rather than just expert opinions (Cooper, 2024, p. 69). Of course, the main concern for many organizations regarding the topic can be the risks involved. Perceived risks can sometimes outweigh the perceived benefits, in that scenario the organization will most likely be even more stagnant on their potential journey towards AI application within their NPD processes.

The risks are discussed in many of the articles that talk about AI adoption in NPD. Comparing some of the listed risks among different sources, it is clear that many of them share the same concerns. In Cooper's article he lists four key areas that include risks in AI adoption which are inaccuracy of results, cybersecurity, intellectual property protection and regulatory compliance (Cooper, 2024, p. 70.). Similarly, same approach is being presented by Witkowski and Wodecki. On their article, the concerns are mentioned primarily as quality of data, meaning the potential bias, inaccuracies, defectiveness or incomplete nature of the data. Also, privacy and security concerns such as transparency with data collection methods, data protection, purpose of data collection and security measures taken (Witkowski & Wodecki, 2024, p. 141). Yet if we take a look at few more articles, on the next one the article itself doesn't focus on the NPD aspect but rather AI solutions in general, yet the same pattern returns. The listed risks are data representation bias, ethical concerns and legal frameworks (Crockett et al., 2023, pp. 779-780). One final article from this sphere we may take a closer look at is reviewing Gen AI (generative artificial intelligence) from the innovative viewpoint. In that article the risks are listed as such, ethical concerns referring to biases, privacy concerns and responsibility, job displacement referring to retaining and advancing in techniques needed for automation and data privacy & security related risks such as robust data privacy and security measures taken for protecting user privacy (Sedkaoui & Benaichouba, 2024, Table 5).

Out of these studies with different approaches and perspectives to AI, shall it be NPD that we are focused on, or something broader like innovation within AI or AI solutions for businesses. The common concerns regarding AI are repeated over these studies which all of them have in common are some sort of result bias or inaccuracy of data, data security concerns or data privacy concerns and often regulatory concerns regarding the data as well. While the choice of words on how it's presented and delivered, the core principles seem to be the same. Job displacement being the anomaly here, it might be worth taking a closer look at.

As we now know the concept of the stage-gate-model and the commonly interpreted gates and stages that have been discussed by various studies. It should be discussed next as to where the biggest amount of uncertainty lies within these stages. According to Cooper, the FFE or also known as the fuzzy front end in NPD refers to the early stages in the NPD process such as ideation, concept generation, market research and technical assessment (Cooper, 2025). In this study Cooper suggests that FFE is the phase where the destiny of the NPD project is decided whether it's going to move forward to meet customer needs and align with the overall business strategy (Khurana & Rosenthal, 1997, as cited in Cooper, 2025). On top of that, Cooper points out that the front end is currently also the stage of the NPD process where the lowest AI application rates occur so far, while the uncertainty in later stages could be better explained with financial- and technical risks (Cooper, 2025). There is also a graph presented that is showing AI implementation percentages in early NPD stages, from there the lowest is "making go/no-go decisions" where AI implementation is basically non-existent currently and second lowest being idea generation where only 2% of businesses apply AI there (Cooper, 2025).

However, in that study Cooper treats businesses as a whole and gives analysis for them from broader viewpoint. Some other studies separate the approach for AI implementation on companies by their size. For example, a study done specifically about

FinTech SMEs will say the following on the matter. NPD studies and innovation process research are mostly concerned with success-factors/variance studies, as well as strategic and stakeholder related matters in bigger organizations (Cubric & Li, 2024, p. 3). Further they will also mention that the traditional linear NPD model doesn't always line up with SMEs because of "different time-to-market requirements, resource constraints or differences in innovation processes" (Berends et al., 2014, as cited in Cubric & Li, 2024, p. 3).

From these studies we can conclude that different approaches can be taken to the overall uncertainty that lies here. While some studies like that of Cooper's bring into light where AI is currently not being applied much in the NPD processes, other studies might recognize the problems and risks that could arise from that. Whilst on the latter study that was presented here, it can be questioned if AI approaches in NPD should be better tailored for different organizations or businesses. The fact of the matter is that uncertainty is necessary now in these early adoption stages, without practical applications there won't be the much-needed empirical evidence for further research.

2.4 Literature Review: Innovation & Creativity

When we delve into the innovative aspects of AI in NPD, we can first seek where the potential innovation lies and what does it means in this context exactly. As we know AI could be used especially for ideation, concept generation and creativity-oriented tasks in the NPD process, but where is the interface between humans and AI?

If we return to one of the articles that we briefly discussed while addressing the risks with AI implementation in NPD, from that article we can also gain some insight into the potential innovation. In this article, it is mentioned that the technology referring to chatbots, have the potential to "restructure organizational structures, enhance human productivity and upset current relationships within the labor market" (Agrawal et al., 2022, as cited in Sedkaoui & Benaichouba, 2024). Furthermore, they also point out that

Gen AI can not only do that but also build new income streams, disrupt company paradigms, further drive strategic restructuring and create new opportunities for innovation as well as economic development (Sedkaoui & Benaichouba, 2024).

From a manufacturing perspective the potential for innovation can be found in the following areas to name a few. Described in an article by Abdelaal, he suggests that AI-powered chatbots can be of help to interact with customers and acquire their order details (Abdelaal, 2024). Mentioning there also that this is a key factor for better digital workplace experience by facilitating repetitive tasks to AI, so that employees can focus on more important tasks essentially (Abdelaal, 2024). Multiple other areas are discussed in the article as to where AI can be applied, but as our focus is on innovation and creativity we might talk about AI-powered design next. About this matter he says that "AI-enabled software can help create several optimized designs for a single product" (Abdelaal, 2024). Essentially, he points out that this software allows engineers to test broad range of different designs against different scenarios and conditions to help them understand better what the best pick is (Abdelaal, 2024). The main force for innovation, however, according to his study, can be interpreted as large language models (LLMs) in the domain of Gen AI. LLMs essentially can be of help when identifying opportunities for designs in manufacturing and creating new complex designs (Abdelaal, 2024). As mentioned on the same page by the author, these LLMs can create cost functions and optimize designs to further enhance manufacturing processes. The reason these factors are important, especially in asset management, is that when the available failure data is scarce, these functions can offer models for predictive maintenance (Abdelaal, 2024).

Another study focused on the matter of AI in corporate innovation, also makes their point about the innovation factor. In this study it is mentioned that AI affects the innovation process by "technological adoption, electronic services, automation and digital transformation of corporates" (Bahoo et al., 2023, p. 4). Information processing is being talked about as a core factor for idea generation stage in corporate innovation. It is said there that new opportunities and solutions can be missed by the organization if they are being held back by technological constraints (Williams & Mitchell, 2004, as cited in Bahoo et al., 2023, p. 4). Essentially, they say that the reason for AI intervention for idea generation is that when a human tries to process large amounts of data it becomes a constraint to collect and analyze the needed data for these new opportunities and solutions that the organization seeks for (Bahoo et al., 2023, p. 4). Another point being made about idea creation in corporate innovation is that human knowledge is limited, so AI can offer radical innovation expertise in corporate innovation process. This means that managers can use technologies such as AI-based automation, networks and machine learning to make new breakthroughs (Posen et al., 2018, as cited in Bahoo et al., 2023, pp. 4-5). Lastly, idea evaluation and implementation being mentioned there on the sphere of corporate innovation, from this matter they say that corporation needs to be able to evaluate and implement the best possible solution for the problem. As to a firm lacking in valuable AI insights, usually it cannot implement the most innovative solutions to the problems (Bahoo et al., 2023, p. 5).

The key takeaways being brought up in these articles that are all examining AI from different angles is that ultimately AI has the ability to shift human focus on the workplaces away from the conventional tasks and jobs onto more administrative or opportunistic objectives. This would be the product of all around technological disruptions in society. What these articles have as a common ground is the way they see AI as the premise for elevated creativity, be it improved decision-making process, transformation in some aspect to help make more innovative decisions or some ways to improve the decisions by better or more knowledge.

However, the context differences and emphasis on all of these articles make it unwise to force disagreements or dissimilarities between these studies. For this reason, it will be more productive to contrast divergences between the approaches of these articles. The first article being referenced in this chapter is studying Gen AI in relation to innovation, the variable here can be considered the approach to human intervention in the study.

As explained by the authors in the conclusion of the study, one key factor enabling the creative human-AI collaboration for new opportunities in the idea generation sector are the “intuitive user interfaces that promote such collaboration and shared understanding” (Sedkaoui & Benaichouba, 2024). The second article referenced in this chapter has its focus on the transformative potential of AI in manufacturing industry, examining the human-machine interfaces in relation to emerging opportunities. As explained by the author of that study, he makes the case for AI to emerge and conquer the manufacturing industry by 2030 with at least substantial economic impact by then (Abdelaal, 2024). The article by Abdelaal takes a predictive stance on the opportunistic viewpoint of what can happen with the help of AI in manufacturing with the help of current data and forecasting of future trends as explained by him in the conclusion of the study. The main domain of innovation as interpreted from his study is that of LLMs in Gen AI and the possibilities that those can offer with the help of more efficient data processing, optimized designs, implementation of advanced cost functions as well as more advanced solutions for designs.

The approach for innovation on the third study referenced in this chapter has its focus on corporate innovation as mentioned previously. However, as also stated in the article, industry 4.0 and AI have transformed business model innovation for all companies, be it SME or corporation (Bahoo et al., 2023, p. 27). In addition to that what they have also brought up in their conclusion is that companies should implement an AI management division to their companies’ internal organization structure.

2.5 Literature Review: Practical Use Cases

In order to get a better understanding of where the interface between AI and humans is, it should be helpful to review different AI use cases in various firms. This will not only help translate the theoretical foundations into practice in real world scenarios, but also to further bridge the theory and practical practice of AI-driven innovation and creativity.

First case scenario that should be reviewed here would be from the book by Marr and Ward exploring different use cases of AI in practice. In that book there is a case about

BMW and how they have applied AI to their product development processes. As explained in the book, most businesses explore AI opportunities in two sectors, them being firstly about integrating autonomy into their business processes to improve efficiency, drive the discovery of new opportunities and streamline the processes (Marr & Ward, 2019, pp. 217-218). Secondly, they will want to find opportunities to integrate AI into their products and services to make them more enticing for the customers (Marr & Ward, 2019, pp. 217-218). Now to the actual use cases of AI by BMW, in the book it is explained that essentially, they have first collaborated with IBM to apply a cognitive computing platform to some of their vehicles which is about learning the drivers' habits and behavior. Furthermore, then the platform will upload the data to the cloud and learn to consider other drivers on the road too (Marr & Ward, 2019, pp. 217-218). Later this system was released to more BMW drivers, as it is mentioned in the same pages that users of their ConnectedDrive app later also got access to it as well. However, this is not the only partnership that they have done with AI, they have also partnered with Intel to presumably explore the opportunities in computer vision technology allowing cars to analyze image data in real-time so that it will be able to react to the world around it autonomously and sharply (Marr & Ward, 2019, pp. 218-220). From these examples within BMW collaborations, it could be considered that the "final product" of the innovation is perhaps yet to come in the future with the help of these kinds of collaborations sharing technology, visions and knowledge. Another viewpoint would be that the innovation and creativity with AI applications in vehicle design is a continuous process which does not have a "final product" but rather follows a looping mechanism in the technological advancement journey in the likes of stage-gate-model where the AI applications to actual products or processes could follow a go/no-go styles of decisions or gates whether the AI application is worth it to pursue further with the concepts.

Considering the innovation factor from these AI use cases of BMW, both collaborations took advantage of predictive analytics with the acquired user data. It can also be seen that their AI applications illustrate how these applications can also help them with their NPD processes. As in early NPD stages it is all about idea generation, concept creation, idea screening and seizing of opportunities. The way BMW is doing its information gathering by doing "field tests" can help them test their ideas and concepts against the uncertainties and manage them better. It the long rung this will help them build their business case via careful and thorough assessment of opportunities in the market. It can also be considered that in the BMW example where the AI application was first introduced as a soft launch to certain vehicles that those were mid-stage go to testing steps in the NPD process where they are moving between development and testing phases of the NPD process before "full launch" or commercialization. The way in which AI usage came in handy in this example was by gathering valuable information about drivers' behaviors and habits that would otherwise be tricky to acquire at mass scale and make these comparisons to other drivers' behavior without cloud and machine learning.

Next case example from the same book with yet vastly different applications and use scenarios would be from the company GE. The book explains that GE has been facing the pressures and expectations of digital data-driven society which aims for sustainable energy (Marr & Ward, 2019, pp. 222-223). As mentioned on these pages by the authors, the solution by GE has been to transform their business strategy and their identity as a company from just an ordinary industrial company now to a smart software and analytics-based company. This has been achieved by taking steps toward machine learning and AI in their processes. The first example on how they have applied these technologies is given from a power plant in Italy, which was not in utilization because of its inability to respond to the changing demands in the industry (Marr & Ward, 2019, pp. 223-225). What was done to this power plant was that they utilized machine learning to sensor data and analyze data from the machinery in the plant to identify and notice causes for inefficiencies (Marr & Ward, 2019, pp. 223-225). That allowed the power plant to become once again active and operating with just half of the environmental footprint it previously had, as explained by the authors. The predictive approach can work as a preventive solution towards the problems before they even became problems because the demands can be considered in advance (Marr & Ward, 2019, pp. 223-225). Second interesting application by GE would be their platform called Predix. Explained in the book, Predix allows them to consider their customers' energy production at a global scale thanks to their global network of their plants, which considers major energy sources from solar and wind farms all the way up to nuclear, goal and gas sources (Marr & Ward, 2019, pp. 223-225). In addition to that, as also explained by the authors, Predix allows them to not only look at data of their own machinery sensors in plants but all of the machinery sensor data in the plants in general. That is how the Predix platform has helped them to equip the so called "digital twin" and be the first company to commercialize it in their strategy. One final example from this company that has already taken advantage of AI and machine learning in a versatile way would be from their business optimization operations as well. As can be guessed, such a large scale industrial global company is going to have very extensive procurement operations, and in those areas, AI could be utilized too. How GE has solved this issue is by centralizing their procurement operations with a help of a software from Tamr, what this software does for them is help them keep track of their purchase history and invoices so that overlaps don't occur by different departments (Marr & Ward, 2019, pp. 223-225). This will promote cost-efficiency and coordination of their inventories.

The GE case demonstrates well how important continuous improvement and adaptation is in today's industry. The company had to delve into the unknown and face the uncertainty before innovation was born. In my opinion the examples by GE illustrate how straightforward and certain uncertainty can be turned when decisions are made based on quality data instead of just hypothesis or assumptions. They have shown us that moving from mid-stages of the NPD process to the late stages of launch to commercialization can be accelerated with the help of machine learning and AI. Their global network of powerplants and Predix are evidence that validation of performance can be tested and optimized before moving to "full launch" of the production or operations. The dynamic all-around adaptation to machine learning and AI by the company has enabled them to be the pioneer of innovation. One key takeaway from their example is that it is not just about how much data and insights can be acquired by

AI, but also how they can utilize that data best to their advantage and make revolutionary decisions with it.

The last example that was chosen to be reviewed comes from the same book of course but this time not from the tech industry but rather consumer goods. In this example the company Unilever has taken advantage of AI in their recruitment operations to save resources and man hours of interviewing time as they say (Marr & Ward, 2019, pp. 118-120.). As presented by the authors of the book here, the recruiting process can be risky and expensive for the company if they end up employing unsuitable people for the jobs (Marr & Ward, 2019, pp. 117-118). The fact of the matter is that the combination of advertising to attract professional hire, screening those applicants and onboarding them is both time-consuming and costly (Marr & Ward, 2019, pp. 117-118). Unilever's solution to the problem was to apply AI to their recruitment process in the following way. The AI application was introduced as a multistage process in which applicants must first send their CV or LinkedIn profile online. What happens after that is they ought to take part in 12 different online games do they wish to continue with the recruitment process. As explained there by the authors, these games were developed by Pymetrics and the point of them is to test the feasibility of the applicant for the roles that they are applying for in different areas (Marr & Ward, 2019, pp. 117-118). Mentioned on the same pages, these games will measure the characteristics of the applicants. One example of how these games work is measuring the risk-taking abilities of the candidate by a gambling type of game, where the applicant must pump air into virtual balloons to fill them as much as possible without letting them burst (Marr & Ward, 2019, pp. 118-120). How the recruitment process continues from here is by submitting a video interview, the video interview is then analyzed by the AI to assess the language, body language and facial expressions of the applicant (Marr & Ward, 2019, pp. 118-120). If the applicant goes on to become hired in the company, they will also gain access to AI-based chatbot which is aimed at helping the new hires gain more information to quicken up their onboarding process at the company (Marr & Ward, 2019, pp. 118-120). Lastly, a little mention about the technology being used. In the interview analysis stage, it is mentioned that facial image analytics technology is being applied there. Computer vision and natural language processing models are used to evaluate the characteristics of the applicant from the interview video, as are natural language models also applied in their AI-based chatbot "Unabot" (Marr & Ward, 2019, pp. 118-120).

The reason why quite a varied example was chosen for the last case was to justify that the product in NPD does not have to be some tangible product, it can also be something intangible like an AI-based digital solution, platform or even an operating model. Product is described as a multidimensional concept, the definition can vary and take many forms (Trott, 2017, pp. 490-491). As mentioned in these pages by Trott, some of the features can be tangible and others intangible. Then the "newness" factor of a product is also a controversial subject because it also has different interpretations. Explained by Trott, some examples that can be considered to propose a "newness" factor to a product could include changing the performance capabilities of the product, changing the application advice for the product, changing the after-sales service for the product, changing the promoted image of the product, changing the ability of the product or changing the price of the product (Trott, 2017, p. 492). In the case of Unilever, the value proposition of AI comes from organizational innovation initiatives that drive the innovation process and data-oriented decision-making steps. This will further help them be more agile and adaptable in their product development processes in the future. While this example was not as directly focused on NPD as the other previously presented case examples from BMW and GE, this example helps us expand our perception of how innovation at organizational level can actuate decision-making in NPD processes too and how those NPD processes are enabled at base level. In the previous chapter, some studies were presented about innovation and why firms might benefit from these AI-based solutions in their organizational structures and information processes. There it was brought up a study by (Bahoo et al., 2023, p. 4) where they suggested that for idea generation the humans can actually be the constraint when they are required to collect and analyze large amounts of data for new opportunities and also that human knowledge is limited, so radical innovation might not be born if being held hostage by these constraints. In the case of Unilever, while the example is not necessarily about idea generation, the same reasoning applies here. They were facing uncertainties such as greater risks for unsuitable recruitment as well as the risk of misallocating their resources such as man hours and expenses. Thus, they were being pushed towards solutions to overcome these uncertainties and create new opportunities at the same time.

All the examples presented here in this chapter are from corporations. That means they have easier access for AI expertise via collaborations with other companies as they can afford to take greater risks and invest more in research and development of these solutions. SMEs on the other hand don’t always have access like that to technological leaps in their processes largely because as mentioned on chapter 2.3 about NPD- and information processes by Cubric & Li’s article. The traditional linear NPD model doesn’t always work for SMEs because of “different time-to-market requirements, resource constraints or differences in innovation processes” (Berends et al., 2014, as cited in Cubric & Li, 2024, p. 3). It should be further concluded that this can be reflected in AI adoption too, as smaller organizations are more likely to face constraints in resources, capital and organizational goals, the AI adoption considerations become a question whether the individual organization perceives the benefits outweighing the costs of uncertainty.

From this point onwards this thesis will continue to compare and apply the theories presented in chapter 2.1 theoretical foundations to interpret and structure the results and findings systematically.

3 Results and Findings

The theories that were chosen to be applied in the analysis of results and findings were the following three theories: Diffusion of Innovations Theory (DOI), Disruptive Innovation theory and Dynamic Capabilities Theory (DCT). While it is true that these theories are often interpreted and applied to explain economic and competitive behaviors, outcomes, implications and processes, the theories are not limited in this sphere. Let's now explain how these theories are applied to distinguish relevant relationships and findings from the literature analysis that comply with the frameworks of the theories.

The DOI theory is a framework to measure the adoption of innovation process in a social system. This system that we are viewing upon in this case is mostly bigger enterprises and their organizational structure because high quality research is mostly available from this realm. However, we can also reflect on and adjust the limited research we have available to also cater smaller organizations on a theoretical basis. One of the key concepts of DOI theory was the adopter categories which we can compare to our practical examples and other findings to find the relationship between the actual real life AI adoption cases and the presumptions of theoretical framework. We can look at our examples from the literature review to find out the reasons as to why some companies might adapt AI in NPD faster while others might be a lot slower or all in all uncertain about the adoption. The innovation-decision process will help us understand why an organization goes from initial heaps of knowledge of innovation to form an attitude towards innovation, decision of continual of the innovation and lastly decision to comply with the decision.

With the help of Disruptive Innovation theory, we can categorize the outcomes of the studies in such a way that we can identify the reasons, premises and implications of what approaches and principles are following the qualities of sustaining technologies, and which ones lean towards disruptive qualities. Values networks can be recognized to solve whether the organizations in our examples are identifying and responding to customers' needs, solving problems, procuring input, reacting to competitors and aiming for profit in such a way that it's driving disruption or inhibiting it. This theory is a valuable tool to compare the linear product development process that was covered in earlier chapters, to more strategic and transformative frameworks of Disruptive Innovation theory.

For the last theory we have the Dynamic Capabilities Theory (DCT), which will be used to measure the enterprises' ability to recombine and reconfigure assets and organizational structures as the enterprise grows, markets and technologies change. Meaning that in this context it will be a very helpful tool to recognize the adaptability of organizations to AI in NPD by identifying their readiness to innovate, learn, react and adapt to the changes provided by the new technology. The way all of this is done is by reviewing the studies with the three core principles of DCT, which are "sensing", "seizing" and "reconfiguring" processes. All of this will help to interpret the effects of AI introduction in NPD.

The objective in the following chapters is to first present the findings thematically then to add a comparative dimension to find the similarities, differences and connections between literature as well as case studies. The thematic approach works a framework to structure the recurring themes, which the comparative approach then serves as an interpretive toolset for each of the themes to add an analytical layer. Previously presented theories will be especially helpful for the comparative part.

3.1 AI in Uncertainty & Decision-Making

Thematic insights from this sector provide us with key knowledge of the factors that have been associated with doubt and indeterminacy in AI adoption within NPD. Across the various literature from the topic, certain topics seemed to reappear and make their presence highlighted in the studies. The first of which appeared in some form in most of the studies are risk management and risk assessment types of concerns. It shall be concluded that different organizations may perceive and specify the risk factors in various distinct ways. Some studies found out that cyber security, intellectual property, inaccurate results or regulatory compliances for example might be some of the risks (Cooper, 2024, p. 70). While others from specific sectors suggested high volume of quality data that requires processing, expectations of what can be achieved by AI – and the approach of people within the organization towards AI solutions, data safety when external companies are connected to the tools and the process (Witkowski & Wodecki, 2024, p. 145). From the practical example of the company Unilever, the risks factors could be interpreted as follows: inaccuracy of results, oversaturated AI interventions and value tradeoffs. What I mean by these is that gamifying the job application process could push some applicants away, letting AI take control of nearly the whole job application process can potentially highlight wrong kinds of qualities in its evaluation of applicants and pushing AI solutions at a short period of time to multiple company processes can cause unnecessary disruption within the organization.

Talking about value tradeoffs, the second theme that was recurring between the studies was measurable value in some form and the organizations' willingness to adapt AI within their NPD processes with little or unclear evidence that the application can offer measurable benefits. As Cooper explains in one of his articles, one of the areas where AI sees notably less applications across organizations is idea generation and "making go/no-go decisions" (Cooper, 2025). Meaning that organizations have not perceived enough measurable value in these areas of NPD with the current evidence of the benefits as compared to the risks associated with. One thing is that different size organizations might perceive the value propositions differently as the traditional linear

NPD model doesn’t always go in line with SMEs for example because of different time-to-market requirements, resource constraints or differences in innovation processes (Berends et al., 2014, as cited in Cubric & Li, 2024, p. 3). Now if we take a look at BMW example, they have essentially put their focus to seeking value from exploring and trying different things before fully committing to them. They are also facing uncertainty just like any other company at first when they are sensing the opportunity to adapt AI in their NPD processes. In their position as a big corporation, they can seize the sensed opportunities into action such as collaborations with other companies like IBM to further reconfigure their processes and operations towards lucrative projects.

The third recurring uncertainty adding factor was data interpretation and handling. As mentioned in one of the studies data representation bias, ethical concerns and legal frameworks could cause concerns with AI applications (Crockett et al., 2023, pp. 779-780). From an innovation focused study some the following factors were brought up: ethical concerns referring to biases, responsibility, keeping up and advancing in techniques needed for automation and data privacy (Sedkaoui & Benaichouba, 2024, Table 5). These studies imply that there is some major uncertainty still within what kinds of data security measures should be taken and how does AI generated solutions comply with the ethical standards of society as well as how these matters should be handled. As what happened in one of our practical examples was that GE had adapted the so called “digital twin” technology in their processes which will help them predict the future energy considerations of their customers globally. The energy industry had started shifting with expectations for smarter and more sustainable, so GE had to reconfigure their business strategy to align with the changing demands. This also gives them more responsibility with data handling and ethical dimensions of the large-scale confidential data that they are now dealing with.

Comparative approach allows us to review the drivers of uncertainty through the lenses of dynamic capabilities to reason the logic behind them. We discovered that most of the uncertainty lies in the early stages of the NPD process such as ideation, concept generation, market research and technical assessment (Cooper, 2025). This aligns well with our findings from studies. However, we also found out that bigger enterprises as compared to SMEs may have different premises, goals and overall business strategies to apply AI within their NPD processes. As seen from our practical examples of the corporations, their successful AI applications within their processes followed the framework of the DCT. This reveals us that the framework of DCT applies for successful applications of AI in NPD processes specifically in bigger enterprises. As compared to bigger enterprises, what SMEs might have to do differently is that they could have to sense the distant opportunities outside of their core domain with greater awareness and understanding of their capabilities and goals to then seize those opportunities into solutions. Their maintaining phase could also vary with different emphasis on whether they need to enhance, combine, protect or reconfigure their assets the most.

What can be concluded from risk management and risk assessment types of uncertainties is that typically the risks are seen differently in various sectors of industries. We know that with proper sensing those risks can be removed from the equation. Sensing can help organizations detect risks through careful search and scan of the technology. Seizing can help organizations evaluate how, when, why and where AI should be implemented in their NPD processes. Lastly, reconfiguring can give future guidelines on how to adjust and be ready for those types of risk. As different firms from different sectors fight against various risks, through the lenses of DCT the comparison will only be about how they will be turned into capabilities instead.

The key points from this section are that the overall objectives with AI application within NPD vary from firm to another as do their factors of uncertainties. As such, the firms can try to follow the general principles of DCT to get a general guideline for competitive growth in their AI application processes within NPD.

3.2 AI as a Basis for Innovation and Creativity

Thematic composition across literature reveals to us that many of the sources find innovative potential within AI applications in NPD. In some of the earlier studies from the literature analysis, we found out that AI usage in NPD can offer new opportunities for better development of product ideas, more innovation in product design, quicker commercialization and better quality of post-commercialization services to name a few (Kakatkar et al, 2020, as cited in Zhang et al, 2021, p. 50). As told by Cooper, the following aspects were listed that have the potential to enhance the NPD process with the help of AI: idea generation, testing of product concepts, acceleration of product creation – physical development and testing of it, to name some of them. (Cooper, 2024, p. 64). From the same article he also pointed out advancement of innovation, meeting customers' needs better with improved product design decisions, more efficient and faster time-to-market in products from datasets to prototyping to eventually design decisions and overall improved product quality (Cooper, 2024, p. 69). All in all, these sources suggested that innovation and creativity can be augmented in many ways, as in many areas of the NPD process from the initial idea generation all the way up to post-commercialization services and activities. Apparently, the room for opportunities is wide in this domain but the question becomes whether firms can access this innovative potential regardless of their position or constraints. To help answer this question we may look at how innovation and creativity is driven in practice.

Mentioned by a few sources was Gen AI and some of its models. As referenced in the literature analysis one of the effects of applying Gen AI in organizations' NPD processes was that it could create new opportunities for innovation (Sedkaoui & Benaichouba, 2024). On organizational level this meant that it could further drive strategic restructuring (Agrawal et al, 2022, as cited in Sedkaoui & Benaichouba, 2024). Also touching this topic was Abdelaal's study from the manufacturing perspective where he told us that the chatbots could come in handy while interacting with customers and their

order details (Abdelaal, 2024). This is a practical example of AI implementation where creativity can take control, however the firm might deem best to their advantage.
Some practical examples from the manufacturing industry where AI can drive innovation and creativity he emphasized as large language models (LLMs) in the domain of Gen AI. LLMs. These can help identify opportunities for designs in manufacturing and creating new complex designs (Abdelaal, 2024). Now moving to our practical example of the company Unilever, they have applied AI to their recruitment process in rather creative and innovative manner. Chatbot technology was applied here as well. With the application of this technology, they have demonstrated a feasible approach for AI innovation in practice that worked for them.

Many of the studies are talking about the potential for AI to drive innovation and creativity in NPD, however not as many firms have applied AI to their NPD processes yet. This leads us to the question of why some organizations adapt AI faster than others and are thus able to pursue innovation faster.

Comparative viewpoint through the lenses of DOI helps us understand how innovators are categorized through the adopter categories. On the Unilever example they are a big corporation that found innovation by being a so called “localite” that adapted innovation within their local domain. They wouldn’t be necessarily placed in the innovator category as it applies to more cosmopolite type of extreme risk-taking small groups or individuals (Rogers, 2003, pp. 282-283). The reason why SMEs and other smaller businesses are not able to be in the first few adapter groups as according to the theory is that the size of the organization plays are role on how much surplus slack resources they have, their total available resources, their employee’s level of technical expertise and their organizational structure to name some of them (Rogers, 2003, p. 441). As compared with the general examples of the literature where innovative factors and benefits are presented if a firm wishes to comply and continue adaptation of AI in their NPD processes, the DOI theory can help explain what principles have been acting as impediments for further diffusion so far. As presented by Rogers, relative advantage is the extent to which a potential innovation is better than the idea that it's supposed to replace (Rogers, 2003, p. 15). A few other principles of the theory tell us that compatibility is the degree to which the potential innovation is in line with the current values, needs and experiences of the potential adopter (Rogers, 2003, p. 15). Complexity is then the perception of how difficult innovation is to understand or adapt (Rogers, 2003, p. 16). These were some of the key principles that line up with the findings of the literature analysis. As discussed in the chapters talking about uncertainty, the perceived risk factors could be wide range of different factors depending on the sector the firm operates in, the size of the firm or their organizational structure. Some of the perceived uncertainties were regulatory, ethical, data-based or intellectual property factors. What DOI tells us is that these organizations that are experiencing these types of unknowns might be unsure because they don't have certain ability to evaluate whether the trade-off would be worth it to replace the old technology, whether the compatibility would align with their values, needs and so on as well as if the AI adoption is perceived as too difficult to apply to their processes.

However, as the theory also points out innovation is a relative measure of continuous variable that is innovativeness (Rogers, 2003, p. 280). Meaning that all these innovator categories are conceptual tools at the end of the day that don't always align with everything that there is to diffusion of innovations. These case examples reviewed examples from successful AI adoption in corporations because the research of the topic is currently lacking for smaller firms. This means that while DOI might suggest that most, especially smaller firms might get positioned in the early and late majority categories as innovators according to the theory, their own choices like managerial decisions, venturesome experiments and expertise can still modify their position as innovators.

3.3 AI in Operational Efficiency & Practice

Thematic observations across practical examples as well as literature have provided us with a comprehensive understanding of the potential, risks, innovation and barriers among many other aspects when it comes to AI adoption in NPD processes. For this last chapter reviewing results, let’s shortly summarize and highlight some of the overall implications of efficiency driving forces. One operational efficiency related dimension could be process-optimization, which we have learnt that AI could enforce automation through the whole NPD process or just some areas of it. Practical examples such as Unilever have demonstrated that AI can handle complex large-scale data and make assessments/decisions considering also aspects that humans might miss or are incapable of evaluating. BMW example has shown us the potentially revolutionary reach of AI in NPD in the future of manufacturing on a technical level, GE example has proven that cost savings, streamlining the supply chain, increasing efficiency and reducing waste can be part of what AI can do within NPD. Another dimension is predictable insights into the future, where all the practical cases have shown that the predicative ability of AI to forecast some aspects of the future will open access for preventive maintenance and more reliable future forecasting as well as planning. Meeting customers’ needs better with improved product design decisions, more efficient and faster time-to-market in products from datasets to prototyping to eventually design decisions (Cooper, 2024, p. 69). This will eventually mean improved product quality and more sustainable competitive growth for the companies as they are able to bring more optimal solutions and products that respond directly or indirectly to customer needs and feedback. Across the many examples that were talked about during this thesis, many of them suggested in some ways that AI can lead to smoother, faster and more reliable Go/To decisions in the stage-gate model of NPD. What this means in practice is that the overall information processes and decision making through ideation, conceptualization, business case creation/development, testing and commercialization if we go by Coopers definition, would potentially see streamlining, transformation and/or centralization.

Comparative take on the practicalities of AI in NPD from the viewpoint of Disruptive Innovation Theory tells us that new technologies are either sustaining or disruptive in nature. If we look at AI implementation from the different case examples, all of them could be categorized to sustaining technologies because they were value-adding in one form or another. Take BMW for example, their AI application added value by enhancing safety and reliability of their products. GE on the other hand had improved value by cost reductions, increased operational efficiency and reduced waste. Unilever saw value in saved manhours, convenience and ability to shift focus to more important tasks by humans. These were of course just some of the current and predicted outcomes for short-term value thus disruptive considerations should be considered as well. When it comes to these examples, traits and signs of disruptive technology might come later down the road. Potential for disruptive qualities might come from the self-directed nature of AI in NPD, where it could challenge the stage-gate model style of NPD into more dynamic and continuous process. Instead of expertise, resources and insights, the change to AI-focused industries could lead to more focus on data driven competition, where those will be the winners who can make their AI process, handle, create and evaluate data best to their advantage. This could also mean that smaller firms without access to strong AI tools in their NPD processes could suffer from a lack of competitive data management. On the other hand, if AI has the potential to disrupt the markets, then theory would also suggest that what is now sustaining might not always be sustaining. Thus, smaller firms could also benefit from the situation if they are able to establish such value networks that ought “to identify and respond to customers’ needs, solve problems, procure input, react to competitors and aim for profit (Christensen, 1997, p. 32). This would take place in a scenario where AI disrupts the distribution of information processing in NPD.

4 Discussion and Conclusion

It came to be the best decision to split discussion and conclusion into two subsections in this chapter. The goal for the discussion chapter is to communicate the reasoning and interpretations of the results & findings, to reflect on what was learned during the previous chapters as well as also to point out potential research gaps. Then the thesis will move onto the conclusion part where I will explain each research question and then try to give summarized and short answers based on what was found out during the results & findings chapter. During the conclusion chapter, there is going to be reasoning given for why this research was conducted, what is the importance of it and what factors motivated this specific research topic as well as few words on the contributions and scope of future research.

4.1 Discussion

Through the results & findings chapters certain themes and connections between the theories stood out the most. One of the recurring themes between all of the theories and findings was the effect of organizational capabilities and resources with the overall adoption success of new technologies. In this thesis practical domain was analyzed through examples that featured bigger enterprises because quality research was still lacking from smaller organizations on their AI adoption in NPD. This leads us to a research gap suggesting that AI adoption in NPD through the lenses of SMEs or other smaller organizations should be studied more with reliable case studies to find out whether the implications of the theories hold true for them, and to determine to which degree their own actions and choices are limiting them or if the limitations are external like some of the theories suggested.

Another topic that should also be considered is whether the traditional linear NPD model will hold true for the future because of AI intervention or will it evolve into something else that requires new theory crafting and more dynamic approach. The results & findings of this thesis suggest that because of different goals, expectations, needs, requirements and situations of AI applications in NPD by various organizations, the known NPD model may not hold up with the test of time.

The uncertainty focused chapter revealed tons of valuable information about the barriers keeping AI from taking over AI faster in organizations as of now. The main barriers based on the literature analysis were doubt and indeterminacy related attitudes towards AI. This chapter had its overall focus on revealing insights about the challenges about introducing AI in NPD as one of the research questions was related to this topic which I will present in greater detail during conclusion chapter. What we learned during this chapter was that organizations tend to perceive the potential challenges differently in forms of various risk factors such as cyber security, regulatory factors, result related accuracy, high volume of data to be processed, expectations of what can be achieved, data safety and external companies' intervention on their AI solutions. We learned that as of now the NPD stages where especially little AI is being implemented are idea generation and go/no-go decisions. What also came up was that organizations of different sizes might have diverging factors such as premises, goals and overall business strategies to apply AI within their NPD processes which explain some of their challenges as compared to bigger enterprises. With the help of DCT through the concept of sensing, seizing and reconfiguring I was able to suggest implications on what approaches can help combat the risks and challenges within AI in NPD by turning the uncertainties into capabilities, which the study was able to offer differing approaches for SMEs.

From the potential of AI in NPD, we learned a ton of what it might be capable of achieving. One aspect were the innovation and creativity accelerating factors such as the potential of AI to take over the entire process from ideation all the way up to post-commercialization services, and with better data processing methods firms will be able to respond to customers' needs better, as such their overall product quality was projected to improve with the help of AI. We found out that different forms of AI technology and language models might serve different purposes. How the DOI theory is related to innovation and creativity was that it helped to explain why some organizations adapt new technologies such as AI faster while others may trail behind. According to DOI firms can be placed into different adopter categories as such we reasoned what characteristics and traits fit in line with our findings. Then we learned that different principles of the theory such as relative advantage, compatibility and complexity which might be some of the key factors in trailing smaller organizations behind currently and affecting their outlook on adapting AI within their NPD processes. However, with the help of the theory we also sort of contradicted these constraints because smaller organizations can still find innovative potential with their own choices like managerial decisions, venturesome experiments and expertise to adjust their position as innovators. This chapter about innovation & creativity was conducted in such a way that it will reveal us information about the overall opportunities of AI in NPD because this was one of the research questions which will be explained in greater detail in conclusion chapter.

The final chapter about results & findings was themed around the operational and practical aspects of AI in NPD, with a goal to bring forward robust useful views about the current as well as the future role of AI in NPD. The chapter highlighted some of the efficiency driving forces of AI in NPD, reflected on the current role through the practical findings and evaluated the future with the help of theoretical findings from literature. The Disruptive Innovation Theory worked as a backbone to the comparison between sustaining and disruptive categorization based on the evidence of what my research had produced and how does the principles of the theory align with these findings. Thus, the thesis was able to offer a multidimensional approach to the future of AI in NPD for the smaller organizations as well which emerged as a potential alternative for the future.

4.2 Conclusion

This thesis included three research questions which were all constructed around the unknown effect of what AI will potentially have within NPD. The goal of this thesis was to structure the bits and pieces of what is currently known around the topic, what are the missing insights, what are the theoretical contributions as well as to clarify this knowledge in such a way that it assembles a clearer picture of the overall fragmented whole. There are a lot of studies done around the topic of AI in a broader societal context such as digital transformation or more technical aspects like engineering and so on. What was noticed-missing are studies about AI's effect on NPD processes that would study the subject in a neutral manner considering both the challenges and opportunities around this dimension. Thus, it was decided to conduct such study that would not only synthesize the scattered missing parts together, but also to offer new insights with the help of DOI, Disruptive Innovation Theory and DCT in the scope of AI in NPD which has not been done previously as to this thesis' author's knowledge. The aim of this thesis was to shed into light some of the key struggles, possibilities, and purposes of AI in NPD now and in the future, so that organizations that consider applying AI in their NPD processes might gain some value from it. Also, this thesis aimed to enrich and contribute to the research of AI and NPD in ways that expand the understanding and discussion around the topic.

The first research question for the thesis goes as follows: In which areas of new product development (NPD) has artificial intelligence (AI) been used and what kind of opportunities does its use offer? According to the findings drawn from the case examples as well as literature, it was found out that AI has been used more on the mid- and late NPD stages instead of the early stages as of now. The case examples demonstrated that development and testing phases of NPD have seen AI utilization in the forms of process optimization and automation activities such as product design optimization, simulations, predicative forecasting of future needs & requirements, streamlining the supply chain activities, predicative risk management as well as planning and decision-making evaluations. The later NPD stages meaning launch and commercialization related activities have seen supportive implications from AI usage such as enhanced information about customers' needs, more efficient and faster time-to-market commercialization of "products" because of improved data management and decision-making as well as more coherent post-launch evaluations of product performance because of real time data analysis of AI. If we consider the opportunities of AI in NPD, the results have provided us with the conclusion that the possibilities are endless as these AI technologies augment human creativity & innovation through the whole NPD process and drive strategic transformation of organizations, the specific areas especially prone to most opportunities are Go/To decisions in the stage-gate model of NPD where information processes and decision making through ideation, conceptualization, business case creation/development, testing and commercialization, would potentially see transformative results from AI applications and/or centralization of these activities.

The second research question was formed to pinpoint the underlying challenges of AI applications in NPD. The research question goes as follows: What are the main challenges in introducing artificial intelligence (AI) in new product development (NPD)? Considering what was conducted from the results & findings, the main issue could be summarized into one sentence "uncertainty of risks and value-tradeoffs between replacing old NPD processes with new technologies such as AI can cause doubt in organizations of their capabilities on their AI application journey." The results have demonstrated that organizations from different sectors and different sizes may perceive challenges much differently to each other. However, most of the results indicate that some of the recurring challenges between most are some sort of interpretations of data privacy/safety related factors, ethical concerns, data accuracy, data handling, data bias, complexity, compatibility, implementation, expertise and financial reasons. The key takeaway was that while bigger enterprises might have challenges with continuous competitive improvement, scattered responsibility in AI through different divisions of the company or modifying their processes too fast/much in a short period of time, SMEs on the other were concluded to have different challenges such as time to market requirements, resource constraints or differences in innovation processes (Berends et al., 2014, as cited in Cubric & Li, 2024, p. 3).

The third and final research question for the thesis goes as follows: How does literature evaluate the role of artificial intelligence (AI) in new product development (NPD) now and in the future? This should be answered in two parts to differentiate the current and future outlooks. As reasoned in results & findings, the current outlook for AI in NPD is considered sustaining because it showed value adding elements through all of the considered examples. However, as discussed numerous times there are still tons of challenges and uncertainties that make it unclear whether it might become disruptive in the future because of different unknowns such as importance of data competition, potentially shifting dynamics of NPD processes and possible AI's disruption on the markets. Overall, it can be said that as of now, AI application in NPD is still very limited in early NPD stages such as ideation and go/no-go decisions. As conducted from the literature it seems like these stages are currently not meeting the threshold for value tradeoffs in such a way that it would supersede human creativity and decision-making for the time being. If we consider the role of AI in NPD in the future, many of the sources highlighted the quickly evolving atmosphere of AI in NPD. The presumptions imply that the whole currently known linear stage-gate model might not apply in the future and instead it may gradually or even rapidly evolve into something that responds to the changing demands that AI could potentially set for the future. Another viewpoint would be that its role is going to be less revolutionary and that it would make some of the current NPD stages more efficient, help with decision-making, enhance product design and allow for faster time-to-market introduction of new products. One key aspect to consider is whether it could become a disruptive technology if the value networks don't align with some areas around AI applications in NPD such as expectations of what it can achieve, meeting customers' needs or mismatch between organizational capabilities. For the conclusion, it should be said that as AI's role continues to emerge and become more important in NPD, this subject deserves continuous research and exploration.

4.2.1 Theoretical contributions

As several practical implications were already discussed and presented during the results & findings chapters as well as conclusion section. Furthermore, this subsection of the thesis briefly talks about the key theoretical contributions towards this subject of research. This thesis reviewed the role of AI in NPD in a multi-faceted scope; thus, one idea this thesis suggests is that the role of AI in NPD is highly tied to uncertainty causing factors, is affected by the size of the organization, is dependent on the specific phases of the NPD process and driven by organizational goals. Secondly, this thesis applied three different theories to synthesize their frameworks in line with the literature that resulted in unbiased, broad and reliable contribution towards the ideas of the challenges, opportunities and role of AI in NPD.

4.2.2 Limitations and directions for future research

This thesis was based on literature analysis of peer-reviewed academic articles, supported with classic key literature around the topic. As such empirical data was lacking which could have contributed to the observations, credibility and objectivity of the thesis. Empirical data from primary sources would be highly recommended for future research on the topic, especially case studies of AI introduction to SME's NPD processes can be of value towards more thorough investigation of the topic. Another limitation of this thesis is tied to time. As we all know AI is currently a rapidly developing technology, because of this the results of the thesis are time-bound.

Currently a key direction for future research of the topic would further elaboration of the SME perspective of AI in NPD. Especially AI's role in different stages of NPD process should be studied with the help of empirical primary data gathered from practical implementations and observations around the topic. Also, longitudinal continuous studies that are reviewing the post-launch outcomes of new product innovations that took advantage of AI in their innovation process could contribute with new insights to the topic.

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Appendices

Appendix 1. List of reviewed articles according to the theme

Author and year	Title of the article	Theme(s) related to this thesis
Abdelaal, M. (2024)	AI in manufacturing: Market analysis and opportunities	Innovation & creativity
Bahoo, S., Cucculelli, M., & Qamar, D. (2023)	Artificial intelligence and corporate innovation: A review and research agenda.	Innovation & creativity, innovation process
Cooper, R. G. (2024)	The AI transformation of product innovation.	Role of AI in NPD, NPD process, risks, stage-gate-model
Cooper, R. G. (2025)	The NPD game is won or lost in the first five plays: How AI can help in product innovation.	NPD process, uncertainty
Crockett, K., Colyer, E., Gerber, L., & Latham, A. (2023)	Building trustworthy AI solutions: A case for practical solutions for small businesses.	Uncertainty in AI adoption
Cubric, M., & Li, F. (2024)	Bridging the “concept–product” gap in new product development: Emerging insights from the application of artificial intelligence in FinTech SMEs.	Organizational uncertainty

Harmancioglu, N., McNally, R. C., Calantone, R. J., & Durmusoglu, S. S. (2007)	Your new product development (NPD) is only as good as your process: An exploratory analysis of new NPD process design and implementation.	NPD process, stage-gate-model
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