Master Thesis

From Innovation to Implementation: The Role of Generative AI in Optimizing NPD Performance

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Preface

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Abstract

The aim of this thesis is to get in depth insights in the drivers by which the use of Generative AI in the New Product Development (NPD) process impacts NPD performance within businesses. Additionally, it explores the interaction between the NPD performance measures (cost, speed, mistakes, and knowledge sharing). By exploring these drivers through seven mini case study and eight semi-structured interviews, this study seeks to provide a comprehensive understanding of how generative AI could enhance NPD outcomes. Several drivers were identified through which genAI usage in NPD impacts the NPD performance measures, such as an increase on efficiency leading to less NPD cost, increasing task execution speed enhancing NPD speed, improving knowledge capture, and finding through a genAI based knowledge repository enhancing knowledge sharing, and less (repetitive) work prone for human error decreasing NPD mistakes. However, genAI tools also introduce a new way of errors, since itself is prone to making mistakes. Furthermore, it brings risk in privacy for sensitive data and poses challenges in integrating into the process. Despite, it shows a lot of potential for enhancing NPD performance. However, implementing genAI tools should not be the goal in itself; it should be used when it adds value.

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Introduction

In the continuing rise of digital technologies, Artificial Intelligence (AI) is on its way to become a key technology of this century and currently is transforming innovation in multiple ways (Brem et al., 2021). AI are complex, self-learning systems that identify patterns in large data sets, that can be used for specific tasks (Brem et al., 2021; Reim et al., 2020; Soni et al., 2020). Several applications of AI in businesses are possible, such as natural language processing (NLP) and computer vision (CV), which are self-learning systems (Brem et al., 2021). Additionally, AI includes generative AI (genAI), which refers to technologies that are capable to interpret and generate new content, such as ChatGPT (Mariani & Dwivedi, 2024; McKinsey, 2024a). Davenport and Ronanki (2018) state that companies benefit from AI in its performance, making better decisions and creating new products.

While AI will also transform multiple aspects of businesses, for New Product Development (NPD), this century AI is possible to be a turning point (Cooper, 2023a). NPD is the process of how a new product, or an existing product is improved by using its capabilities and resources and is considered highly important for business success (Brown & Eisenhardt, 1995; Marion & Fixson, 2021).

AI could change the NPD landscape, since nowadays, only 30% of new-product projects are a commercial success and the technology is likely to improve agility, efficiency, or productivity. This will ultimately increase the successes in NPD (Cooper, 2023a). For example, General Electric states that they cut the design process for engines and turbines at least in half using AI (Bogaisky, 2019). Since NPD has such a low success rate, it is important to examine which drivers influence NPD performance, and what impact genAI use in NPD has on these, to determine how genAI use can enhance NPD outcomes. Next to low the success-rate in NPD, firms do not fully understand AI, despite the general understanding of AI's potential, which prevents businesses to implement AI related solutions and leverage it to gain business value (Ransbotham et al., 2017).

Barbalho and Rozenfeld (2008) found several drivers of NPD performance, important for NPD success, influencing multiple performance metrics, including an early and sharp product definition and early market test. For instance, early and sharp product definitions could streamline the development process. This study builds on this previous research by examining if the use of genAI in NPD processes can enhance these known NPD drivers, leading to better NPD performance.

Research has been conducted on the integration of AI and other digital innovation in the NPD processes (Brock et al., 2020; Rao et al., 1999), and what applications occur in NPD (Bouschery et al., 2023; Füller et al., 2022). Also, research has been done on the topic of NPD success, performance and AI use (Cooper, 2023b; Zhang et al., 2021). In addition, there are several drivers which influence NPD performance (Barbalho & Rozenfeld, 2008). However, a gap exists in current literature what the underlying drivers are, through which Generative AI use in NPD impacts NPD performance.

Therefore, the aim of this research is to get in depth insights in the drivers by which the use of Generative AI in the New Product Development (NPD) process impacts NPD performance within businesses. Additionally, it seeks to analyze how Generative AI relates to the drivers known to influence NPD performance and will explore the interaction between the NPD performance measures. By investigating these drivers, this study seeks to provide a comprehensive understanding of how generative AI contribute to enhancing NPD outcomes, thereby informing both practice and theory.

The research question is: *How does the use of Generative AI tools during the New Product Development process impact New Product Development performance within businesses?*

Cooper (2023a) describes that AI is going to change all aspects of business, especially NPD. However, next to examples of what AI is going to change and a few specific performance related studies, it remains unclear what currently the drivers are, through which AI use in the NPD process impacts NPD performance. This research will contribute by exploring what the underlying drivers of NPD performance are. Also, with consideration to what performance drivers are found to be most important and, what opportunities, risks and challenges using genAI in NPD pose.

For businesses, the use of genAI in the NPD process will cause and is causing implications and changes. These businesses could benefit from this study's findings since it will provide insights in previous applied AI in NPD and its influence on the NPD performance, and what the underlying drivers are. This will contribute to understanding AI, which is found to be a problem (Ransbotham et al., 2017). In addition, it will give insights in best practices, implications, and challenges, which will be enlightening.

To make these contributions, in the next chapter we will dive further in the relevant literature on these topics and how the topics relate, before continuing in the next chapter on the method and chosen approach. In the following chapters we present the findings, followed by the conclusions, discussion, contributions, and limitations.

Theoretical framework

Artificial Intelligence

In the last few years AI gained popularity, certainly since the rise of ChatGPT. However, the first time the term had been used was in the 50’s, after which the concept of computers having feelings has fascinated and scared everyone thoughts. Even though since then, AI became a promising technology (Bini, 2018). When we look at the present, AI can be defined as intelligent systems designed to execute specific tasks using data, analysis and observations without requiring explicit programming (Reim et al., 2020). Furthermore, AI contains the characteristics of self-learning and the difficulty to understand (Brem et al., 2021). However, in the contexts of businesses, AI is described as empowering machines to adapt to their environment and have the ability to identify correlations, characteristics, and correspondences in large amounts of data (Brem et al., 2021; Soni et al., 2020). In recent years this progress is made due to reduction in costs associated with digital technologies for data acquisition, storage, processing, and analysis, coupled with improvements in the performance of algorithms (Brem et al., 2021; Soni et al., 2020). Furthermore, Mishra and Pani (2021) describe AI as a new wave of information technology (IT) as information-based systems that can be used in analytics, visual processing, language processing. In this research we look at AI as complex, self-learning systems that can be used to identify patterns large data sets, widely applied across multiple domains, driven by algorithms. Because it is explorative research, we keep a broad view and use aspects of multiple definitions. However, we can take a more in-depth look at several AI-tools.

Generative AI (tools)

When we take a further look at the applications and tools of AI, there are numerous options. Next to the analytics, visual processing, language processing described by (Mishra & Pani, 2021), Brem et al. (2021) describe, next to computer vision (CV) and natural language processing (NLP), deep learning and machine learning as applications of AI, that in general rely on statistical models. Furthermore, Mariani and Dwivedi (2024) suggest that generative AI (genAI) is a broad term that consists of AI systems that are capable of generating high-quality content such as text and images, using the data which the models are trained on. The rise of deep learning, a subfield of machine learning, led to the enhancement of those generative AI models and now serves as the primary framework for NLP and CV (Mariani & Dwivedi, 2024)

So, CV and NLP are examples of generative AI, which is AI that has capabilities such as generating text (NLP) and images (CV), spanning various forms such as writing texts and making artwork, making use of a prompt to create content in response to it (Davenport & Mittal, 2022; McKinsey, 2024a). The underlying mechanisms involves complex machine (deep) learning models to predict the 'next' word or picture.

Thus, both CV and NLP could possibly be considered examples of generative AI. Companies most likely use OpenAI's ChatGPT, Google's BERT and BARD, Midjourney, Dall-E, and Microsoft's CoPilot, which might give these companies a wide variety of options to use it for value creations (Chui et al., 2023; Davenport & Mittal, 2022; McKinsey, 2024b). While Computer Vision (CV) and Natural Language Processing (NLP) are typically associated with tasks involving analysis of input data rather than generation, this research uses a broader interpretation of 'generative AI'. It acknowledges that certain applications within CV and NLP, such as ChatGPT, can not only analyze input data but also generate new content based on learned patterns. Therefore, the term 'generative AI' in this research overarches both the generative and analytical capabilities of CV and NLP technologies.

NPD and AI

New Product Development (NPD) is the process of how a new product, service or method is introduced, in which both the outcome and the process should be considered (Marion & Fixson, 2021). The process of product development is regarded one of the crucial processes for the success, renewal, and revival of businesses, especially for those in a dynamic environment and which operate in high-competitiveness markets (Brown & Eisenhardt, 1995). The NPD process consists of five stages, as Cooper described in the Stage-Gate model, widely used in NPD as a map for new product development. The stages consist of concepting to launch (Cooper, 2008). Cooper and McCausland (2024) use 5 stages, concept, building business case, development, testing and validation and lastly, commercialization and launch. He uses four overarching concepts: frond end, development and testing, back end, and post launch. The frond end includes, next to concept and building business case, also idea generation. After development and testing, the back end consists of commercialization and launch. Furthermore, he adds post launch which includes customer feedback and performance monitoring (Cooper & McCausland, 2024).

However, according to Cooper (2019), the Stage-Gate model is not one size fits all. Minor projects can require less stages whereas it is more likely that major and riskier projects use all five stages. In this research we looked at the NPD from the front end of NPD through development and testing, the back end and post launch since this process is different at most businesses and not all stages are used in every business.

According to Zhang et al. (2021), AI usage in the NPD process increases project success. In comparison with not using AI in a project, the success rate increased in all stages of a project when AI was implemented. They suggest that organizations should embrace, promote, and invest in AI usage for NPD since it reduces failure rate and increases NPD success. Furthermore, Füller et al. (2022) suggest that there are several applications of AI in the stages of NPD. As discussed in the previous paragraph, multiple applications of AI are possible. Füller et al. (2022) found that NLP, CV, and machine learning are found to be helpful in several stages of the NPD process. More specifically, in the idea generation phase, AI was used to generate several ideas such as graphical designs for logos. In the idea evaluation and selection phase, AI was used to support the selection of best product ideas by identifying which were the most important product features, using a machine learning algorithm. In the concept and solution development phase an example is the use of generative design applications that help finding design options and optimization of aspects, such as materials. Lastly in the launch and implementation phase, they found that AI may help get insight in the customer data, for example to enhance targeted advertising (Füller et al., 2022). Furthermore, Cooper and McCausland (2024) state that there are already over 40 unique AI applications for NPD, which varies from market research to design. Zhang et al. (2021) describe ai use as the deployment of AI technologies in the NPD process by an innovative team, to support decision making or other innovation tasks.

NPD Performance

To assess NPD performance, Awwad and Akroush (2016) suggest five dimensions of NPD performance: NPD capabilities improvements, NPD internal learning, NPD knowledge sharing, NPD marketing measures and NPD financial measures. Additionally, one of the main aspects of NPD processes is knowledge sharing (Brown & Eisenhardt, 1995). Brown and Eisenhardt (1995) underscore the importance of frequent communication and integration across different functions for successful product innovation. Yet, Cooper (2023b) examines time-to market, productivity and efficiency, mistakes, agility/responsiveness, and decision-making to measure NPD performance. Given that AI improves *speed or reduces time-to-market*, lead to *fewer mistakes*, and facilitate *cost reduction* (Brem et al., 2021; Cooper, 2023b), this research looked at these performance dimension. In addition, *knowledge sharing* was used as fourth NPD performance dimension. This consists of exploitation and exploration, in which exploitation is about using what we already know in similar situations, like capturing, transferring, and applying existing knowledge, and exploration, on the other hand, is about sharing, combining, and coming up with new ideas or knowledge (Akroush & Awwad, 2018). It can be defined as activities that facilitating learning-oriented activities, empowering the exchange of knowledge, and enhancing collaboration, knowledge sharing, increasing the ability to achieve both organizational and personal goals (Awwad & Akroush, 2016).

Drivers of NPD performance

Barbalho and Rozenfeld (2008) identified several drivers of NPD performance in current literature. Among these, that might be particularly relevant to this study's theoretical framework, include strategic resource orientation, which may play an important role in allocating resources effectively to NPD projects, potentially impacting factors such as speed and cost reduction. Furthermore, an early and sharp product definition can streamline the development process, leading to a faster NPD process. Customer tests of products can provide valuable feedback early in the development cycle, facilitating adjustments and improvements, which could contribute to the speed of NPD. Communication and collaboration into new product projects could foster a culture of teamwork and idea exchange, which may positively influence knowledge sharing. Lastly, early market tests enable companies to validate product concepts and identify potential issues before full-scale launch, potentially reducing the likelihood of costly mistakes and speeding up the NPD process.

When we take a further look at possible drivers through which NPD performance increases by using generative AI in the businesses NPD process and using some of the drivers above mentioned, the use of generative AI may enhance the NPD process speed through faster analysis of larger datasets, the acceleration of iterations or feedback loops using NLP, and/or automation of tasks.

Second, mistakes could possibly be reduced by the automation of (repetitive) tasks prone to human error and thereby reducing the chance of mistakes. Enhanced insights using NLP analytics could provide help in identifying and preventing potential errors in the NPD process.

Cost savings could possibly occur by enhancement of the NPD process speed through automation of task leading to fewer labour cost, or a faster time-to-market leading to earlier product income. However, this may also be due to more efficient resource using genAI planning and prediction in resource allocation

Knowledge sharing and collaboration within teams may be stimulated through enhanced communication. GenAI may enhance communication by enabling more efficient information sharing and collaboration on projects. Furthermore, it may lead to leverage of hidden knowledge (sources) within organizations, which could enable teams to better make use of each other's expertise.

Additionally, in an exploratory manner, this research will investigate whether such (known) drivers are applicable in the context of genAI use in NPD and explore drivers not identified in the existing literature.

Methods

Research method

This study employs a qualitative approach to explore and understand how genAI use in the NPD process impacts NPD performance is, aiming specifically to explore the drivers of NPD performance. Within this research, a multiple mini case study method has been selected as the primary research design. As stated in (Yin, 2009), case studies offer the opportunity for in-depth exploration of a topic is, something often unattainable through surveys. Given our aim to gain such in-depth insights into the dimensions previously outlined, the case study method aligns well with our research objectives. Furthermore, Yin (2009) emphasis the superiority of case studies historical studies for investigating real-time events as there is direct engagement using interviews and observation. Since genAI use in NPD is relatively new and certainly real-time, case studies emerge as the preferred approach. In addition, the choice of case studies over experiments is underscored by the argument of Yin (2009) that case studies are more appropriate when control over behavioral events is unnecessary. In the context of this research this control is not applicable nor required. However, the initial plan was to us a multiple case study method. Due to difficulties finding informants, this led to a forced choice to do a multiple mini case study.

Case selection

Seven mini cases have been selected, based on their (intention to) use genAI (NLP and CV) in their NPD process. To be able to make comparisons between the cases it is required in the replication logic to obtain a certain number of cases to enhance this comparison (Eisenhardt, 1989). Since Eisenhardt (1989) recommends between four and ten case studies used in such research, this research contains seven mini cases, in the middle of the spectrum advised by Eisenhardt (1989). Furthermore, when looking at criteria for the several cases, in the context of this research, it is important that the company uses or has the intention to use genAI (NLP and CV) in their NPD process, to investigate which drivers influence the impact of genAI use in NPD on the NPD performance. Even though the intention was to only investigate four cases in which genAI is used, due to difficulties in finding companies willing to cooperate in this research, the explorative nature of this research, combining with time constraints, in two cases genAI is not used in the NPD process, yet. Both companies do not use it for the sake of privacy/data leak reasons but do have the intention to use it. Unfortunately, these difficulties in finding informants, also led to seven cases instead of four. Lastly, theoretical sampling was used in this research, as this will extent the emergent theory, by selecting cases that are extreme or different from each other (Eisenhardt, 1989). This approach enables a comprehensive understanding of the drivers that are explored in the impact of genAI use in the NPD process on NPD performance.

Informant	Case	Company	NLP and/or CV in NPD	Role	Code
1	A	Food machine company	Yes	R&D manager	I1-A
2	B	Geotechnical company	Yes	Data expert – software developer	I2-B
3	C	Electronic company	No	R&D manager	I3-C
4	B	Geotechnical company	Yes	Business intelligence worker	I4-B
5	D	Software company	Yes	R&D manager	I5-D
6	E	Beverage machine company	Experimenting	R&D manager	I6-E
7	F	Transportation company	Yes	R&D manager	I7-F
8	G	High-tech company	No	R&D manager	I8-G

Table 1: Cases (anonymized)

Document	Case	Page	Use	Code
1	A	About us	Product description	D1-A
2	B	Our mission and vision	Product description	D2-B
3	C	Our history	Product description	D3-C
4	D	Home page	Product description	D4-D

5	E	About us	Product description	D5-E
6	F	About us	Product description	D6-F
7	G	Home page	Product description	D7-G
8	-	Blog	genAI tool information	D8

Table 2: Documents (anonymized)

Data collection

Eight semi-structured interviews have been conducted, since it has the advantage of being in control what is addressed during the interview, while the informants can choose their own words (see *Appendix A* for interview guide). In addition, the same questions are asked to multiple informants, increasing the reliability (Bleijenbergh, 2022). These in-depth interviews were conducted with R&D managers and other innovation workers since they were the persons involved in the NPD processes within the businesses. At six cases, one interview was conducted and at one case, two interviews were conducted with two informants that have distinct roles in their NPD (*table 1*). Since not all cases use genAI in their NPD process, some interviews were hypothetical. This means that informants were asked about their expectations. Based on the extent of genAI use, most interviews were also in a hybrid form: partial based on factual experiences and partial on expectation. In addition, documents (websites, *table 2*) were analyzed to retrieve additional information about the businesses and a tool. One observation (O1-B) was conducted to see how NPD was performed using a genAI tool. Therefore, even though we used mini cases, it was possible to differentiate. This triangulation, using multiple data collection methods, leads to enhanced validity (Myers, 2019). *Table 3* is an overview of the operationalization, outlining the constructs, dimensions, items, and their sources. This framework served as the foundation for the development of the questionnaire, ensuring that relevant aspects of this research are adequately addressed.

In *table 3*, a visualization of the operationalization is given based on established frameworks and literature. First, we look at Generative Artificial Intelligence (gen AI), existing of tools such as ChatGPT and DALL-E for Natural Language Processing (NLP) and Computer Vision (CV) (Brem et al., 2021; Davenport & Mittal, 2022). Thereby, we continually look at which tools are found to be useful (and when) and whether these tools are perceived to be accurate.

AI use in the NPD process is operationalized as its influences on decision-making and innovation tasks (Zhang et al., 2021). Furthermore, NPD performance measures, include cost reduction, speed, mistake reduction, and knowledge sharing (Awwad & Akroush, 2016; Brem et al., 2021; Brown & Eisenhardt, 1995; Cooper, 2023b) These are operationalized to assess the outcomes of gen AI implementation in the NPD process and to investigate drivers of these measures. Informants were asked how genAI use changed or could change the performance measures. Cost in percentage of cost before genAI use, speed in percentage of time before genAI use, mistakes in change of amount before and after genAI use. In terms of knowledge sharing, we examined the frequency, quality and engagement of the knowledge sharing within the company, as well as with/to external parties.

Finally, known drivers; based on research of Barbalho and Rozenfeld (2008), we look at early and sharp product definition, customer test, strategic resource orientation, communication and collaboration and early market test. First, early and sharp product definition is operationalized as ensuring a clear and precise product concept early in the NPD. Second, customer test is examined as the effectiveness of engaging customers in testing product(ideas) that can provide valuable feedback. Then, strategic resource orientation entails allocating human and material resources effective throughout the NPD process. Fourth, communication and collaboration are considered the effectiveness of communication and collaboration within the NPD team. Lastly, an early market test is operationalized as the effectiveness of market tests in gathering insights for product improvement. In exploring these drivers, informants were therefore asked whether the use of generative AI in the NPD process could enhance them.

Construct	Dimension	Item	Source
Generative AI	Tools such as Dall-E and ChatGPT	Usefulness and accuracy	(Brem et al., 2021; Davenport & Mittal, 2022)
GenAI use	Deployment of genAI tools in the NPD process	Support decision making or other innovation tasks	(Zhang et al., 2021)
NPD performance	Cost	Change in %	(Brem et al., 2021; Cooper, 2023b)
	Speed	Change in %	(Cooper, 2023b)

	Mistakes	Change in amount	Idem
	Knowledge sharing	Frequency Quality Engagement	(Awwad & Akroush, 2016; Brown & Eisenhardt, 1995)
Known NPD drivers	Early and sharp product definition	Ensuring a clear and precise product concept early in the NPD	(Barbalho & Rozenfeld, 2008)
	Customer test	The effectiveness of engaging customers in testing product(ideas) that can provide valuable feedback	Idem
	Strategic resource orientation	Effectiveness of allocating (human and material) resources throughout the NPD process.	Idem
	Communication and collaboration	Effectiveness of communication and collaboration within the NPD team	Idem
	Early market test	The effectiveness of market tests in gathering insights for product improvement	Idem

Table 3: Operationalization

Data analysis

The data collected through eight semi-structured interviews, documents and one observation, were subjected to cross-case pattern analysis, a qualitative data analysis technique commonly used in case study research (Eisenhardt, 1989). This approach involves identifying patterns across multiple cases to draw conclusions and give insights. The use of multiple mini cases enhances the ability to do a cross-case pattern analysis, since there are more cases.

In coding, first, the data was organized in the dimension of the NPD performance measure. Next to that, AI use in NPD and no AI use in NPD (therefore hypothetical impact) were taken in consideration to investigate the performance. In the third layer of codes, the emerged and known drivers were coded. In addition, performance measures were organized into codes, after which they were divided in separate code: the type of interrelationship, positive or negative, or no identified relationship. Lastly, the themes of risk, challenges, opportunities, hybrid team/tool, most important performance measure and query/prompt were divided into separate codes (A*ppendix B*).

Furthermore, through comparison of the data, the aim was to gain insights into overarching relevant patterns. Miles and Huberman (1994) argue that by applying pattern codes, researchers can highlight recurring things in the data, which leads to a better understanding of the underlying principles within the data.

Lastly, in this research, ATLAS.ti was used for coding the data, since this software offers enhanced efficiency and enforcing a specific coding format is an advantage, which enables to replicate work more reliable at different levels of coding en helps to systematically organize data (Bleijenbergh, 2022).

Limitations of the method

A limitation for this research is the number of informants that have been interviewed. Since it is such an explorative topic, there are preferably many more informants to contribute to the different insights that come from various perspectives. Additionally, Eisenhardt (1989) argues that specific case data is possibly not widely applicable. This decreases the generalizability. In addition, in comparison to unstructured interviews, semi-structured interviews tend to have less room to elaborate answers which might have an negative effect on the validity (Bleijenbergh, 2022).

Research ethics

Boeije (2010) describes three ethical principles to which researchers must act. First, informed consent, which entails that informants should be aware of the nature of the data collection and purpose. Before conducting the interview, informants were asked permission for recording and using the data in this research. Second, privacy. Individuals should decide themselves to whom they give data and to what extent the researcher is allowed to share this data. By beforehand asking for permission and informing them, informants were able and allowed to make the decision whether to share data. Lastly, confidentially, which refers to how privacy is ensured and to anonymity of informants, which was applied by anonymizing the data concerning the respondents and ensuring confidentiality (Boeije, 2010).

Furthermore, data management, storing and sending data, are very important topics. Since this research entails sensitive data such as names and company/product information, it is important to take into consideration the safety of this data. This means that data is managed according to LibGuides (2023). This entails not using commercial cloud storage or USB drive or other portable drives to prevent losses and leaks, and therefore, we made use of local drives and RU Microsoft 365 Teams (LibGuides, 2023).

Results

In this chapter, the results of this research are presented. The analysis focuses on the impact of genAI on the NPD process. The findings present whether known drivers are influenced by genAI usage, new drivers of NPD performance and interaction between the performance measures.

NPD and genAI usage

All cases have different products in different industries and different NPD processes, consisting of different phases. Most informants stated that indeed, the NPD process starts with an idea or a problem which is faced, after which is sought for a solution and ended with a product launch and servicing/maintenance post-launch. Some of the companies use a sort of template for NPD and some have less strict guidelines for NPD.

In the first case, the NPD process starts with identifying problems through customer feedback, generating ideas, followed by screening those ideas, conducting literature studies and quick hand calculations, analyzing the physics involved, determining financial feasibility, developing, and testing concepts, conducting measurements and tests, developing new processes or techniques, strategizing marketing and business analysis, and finishes with the launch. The informant (I1-A) explains that both ChatGPT and CoPilot are used during the idea generation, analyzing the physics, developing concepts but is also likely to be used in other phases since everybody has it open on their screen most of the time. Furthermore, tests with Topology Optimization for mechanics are conducted in concept developing. Lastly, they are developing a knowledge base, based on Large Language Models (such as ChatGPT) enhancing the documentation accessibility. The products they develop, consist of both hardware and software, and it meant for the food industry (D1-A).

In case two, the informant (I2-B) states that the process is different for each product they make, because they make technical applications for multiple geological research purposes (D2-B). It, mostly starts with goal setting through customer consultation, agile team-based beta product development, iterative testing internally and with end-users, and refining based on feedback from beta customers, after which the product is launched at the beta customer. However, the other informant (I4-B) explains they use a stricter template, consisting of market intelligence to assess opportunities, followed by R&D evaluating feasibility and development. Marketing plans the campaign, sales teams are trained, and organizational enablers ensure readiness. Finally, market feedback is collected post-launch. It is interesting that they both view a different process. This could be due their difference in role (I2-B data expert/software developer and I4-B Business intelligence worker). It emphasis the flexibility of the process within the company, depending on different needs and priorities. Both informants (I2-B and I4-B) use ChatGPT in most of their task. One Informant (I2-B) illustrates ChatGPT is used on a personal level in the company and uses it in multiple stages, to ask for solutions and ideas, but mostly for software developing (O1-B). The other informant (I4-B) extensively uses ChatGPT throughout various phases, as a sparring partner to refine ideas, evaluate framework and gather market information such as for competitive analyses. They emphasize caution for sensitive data (ChatGPT input) and verifies ChatGPT's outputs.

In the third case, a template is followed during their NPD for all types of electronics (D3-C), as the informant describes (I3-C). They follow a 7-step model: technology development, concept development, detail design, design verification, pre-production (pilot series), qualification, and production phase. In their NPD, they currently do not use genAI tools due to concerns about data security. They have initiated pilots to assess the risks involved before potentially integrating these tools into their workflow. Furthermore, the respondent (I3-C) is eager to use genAI (more specific ChatGPT) and uses it already privately.

In case four, the company produces software applications for several sectors (D4-D and I5-D). Their NPD starts with business process modeling and event storming meetings to detail processes. Epics are then defined, consisting out of stories. Every quarter, a Product Roadmap is created to make quarterly goals and plan sprints, with deliveries of functionalities after each sprint. The informant (I5-D) explains that ChatGPT is used during estimation of needed time, using historical data for new product development. It's also employed in writing documentation, creating requirements, validating code, and even generating parts of code for development to see whether the code is useful for the eventual code.

In the fifth case, the NPD process of their beverage machinery (D5-E) begins with ideation, followed by a business case evaluation. After assessing feasibility, they move on to concept creation, prototyping, and pilot series. Thereafter comes production and product launch. Post-launch, customer feedback leads to further development and maintenance phases, as the informant (I6-E) mentions. Furthermore, the informant clarifies that they do not structurally make use of generative AI tools. Only in translating documents ChatGPT is used often and experiments take place to retrieve technical information, which according to the informant, is not used in any of their NPD-stages.

Sixth, the informant of case 6 (I7-F) describes that in their product in the transportation industry (D6-F), the NPD process starts with ideation and a project initiation document, followed by prototyping, process design, launch and ending with continuous improvement throughout the product life cycle. The informant (I7-F) rarely uses ChatGPT and furthermore there are a few colleagues using it in for example policy development (ChatGPT) and visuals (Dall-E) for a product presentation. However, it is not extensively used in their standard NPD but used by a few team members for specific tasks not mentioned (due to insufficient questioning), rather than across all phases.

In case seven, for their high-tech product consisting of both hardware and software (D7-G), the NPD process includes a business analysis, problem definition, solution development involving hardware software and mechanics, detailed definition, testing and production ramp-up according to the informant (I8-G). Furthermore, they do not use any genAI tools due to concerns over data and information leaks. They are exploring potential use in the future, especially for repetitive coding task but are in await of approval from their parent company.

Drivers of NPD performance

As explained previously, the NPD-performance measures used in this research are cost, speed, mistakes, and knowledge sharing. Furthermore, drivers through which these performance measures are influenced using genAI tools in the NPD process, are explained in the following section. These consist of previously known (in the literature) drivers of NPD-performance, to see whether they are applicable in the context of genAI usage, and newly identified drivers. The 'existing' drivers of NPD performance are an early and sharp product definition, customer test, strategic resource orientation, communication and collaboration and early market test.

Cost

All informants agreed that the use of genAI in the NPD process led to or hypothetically leads to less NPD cost, due to drivers which will be explained below. Informants found it almost impossible to say or estimate to what percentage cost reduction using genAI in NPD led or could lead. Only one R&D manager (I3-C) dared to do an estimation and estimated that development costs could cut in half, if genAI will be integrated properly. This cost reduction is achieved due to several drivers. First and foremost, less man-hours are and hypothetically could be needed through more efficient work. This approach consists of simply needing less man-hours (labour costs) for tasks during several tasks in the whole NPD process, using ChatGPT, according to two informants from the second case (I2-B and I4-B):

“If you look at the costs, they pay me and (name) in terms of hours, then we save costs. Yes, because I think we can complete more tasks within an hour than we normally could. So in that sense, yes” Quote 1 – I3-C

Hypothetically, according to several respondents (I1-A, I5-D, I6-E and I8-G), cost will reduce in the future by increasing task efficiency among colleagues. For instance, faster software coding, using ChatGPT, in the development phase (I5-D), smarter and more effective work across multiple phases using genAI (I6-E) and using ChatGPT in writing (test) code to enhance efficiency and reduce chance on errors (I2-B and I8-G).

“If you write code that is better, you need less rework on it later. That is cost-saving on itself.” Quote 2 – I2-B

Secondly, multiple informants (I3-C, I4-B, I6-E and I7-F) noted that they hypothetically need to hire fewer external parties since they can be replaced by GenAI tools. For example, document translation throughout the complete NPD process (I7-F) and perform market research during the market intelligence phase, instead of purchasing external reports (I4-B). Additionally, ChatGPT could be used to write requirements and standards, potentially replacing the need to hire external consultants:

“He simply provides a table showing the standards and regulations for these markets, including safety requirements that need to be met. I thought, “Wow, ChatGPT can do this.” Quote 3 – I3-C.

Using genAI in *strategic resource management* could potentially reduce NPD cost. Three informants (I5-D, I7-F, I8-G) suggest that it hypothetically could play a role in the project management or human resource, though they lacked specific arguments or examples, possibly due to how the question was posed. However, for example:

“Yes, that could indeed help, planning tools that are actually based on AI. (…) That will indeed, yes, contribute to the project management section. Yes, that could indeed help, yes.” Quote 4 – I8-G

Most informants (I1-A, I3-C, I4-B and I6-E) believe that genAI does not currently, nor will it hypothetically in the future, play a significant role in resource planning within NPD, as an informant states:

"Well, I don't really see it (genAI tools) as a significant added value for resource planning (in NPD)." Quote 5 – I3-C

Accordingly, we propose:

Proposition 1a and 1b: The use of genAI tools in the NPD process (hypothetically) leads to more efficiency, leading to less NPD cost (1a), and (hypothetically) leads to fewer external parties necessary in the NPD, which lead to less NPD cost (1b).

Speed

All participants indicate that the use of generative AI in NPD either currently leads or hypothetically will lead to a faster NPD process. Informant I1-A describes that Copilot and ChatGPT use currently saves a few hours a week, primarily by assisting with smaller tasks such as script setup and brainstorming in the initial phases of the NPD. In the second case, informants I2-B and I4-B both consider use of genAI tools leading to faster NPD processes. Informant I2-B suggests that using ChatGPT in coding during product development reduces up to 30% of software development time, but this applies specifically to the product development instead of the entire NPD process. Meanwhile, informant I4-B explains that ChatGPT simply make certain tasks faster, although does not know how to explain why. In case 3, the informant (I3-C) says using ChatGPT across various phases hypothetically speeds up the execution of more specific task. Another informant (I5-D) describes that ChatGPT use in software coding currently leads to a reduction less then 10% but is likely to increase to 25% when it becomes more useful and increasingly integrates. In case six and eight, the informants (I6-E and I8-G) think that the use of genAI (most likely ChatGPT) hypothetically speeds up NPD software development. Therefore, we see a pattern in the cases that genAI usage leads to an enhanced task execution speed, leading to an overall faster NPD-process.

Furthermore, a returning theme is that genAI usage could, as previously mentioned, hypothetically reduce the need for hiring external parties. Therefore, two informants (I2-B and I6-E) suggest they also potentially do not have to wait for externally hired parties:

"Within half an hour, you have those answers (from ChatGPT), whereas if you rely on external parties who might be busy, it isn't strange that you could be two months further…" Quote 6 – I2-B

Additionally, in changing NPD speed, three ‘known’ drivers could possibly contribute. First, also strategic resource management. Second, an early and sharp product definition and thirdly, customer test.

For *strategic resource management*, informants responded more or less similar to the role of resource management in improving speed in comparison to reducing cost (in the context of using genAI), however more positive. All informants do not state that genAI currently has helped in resource management. Some informants (I2-B, I5D, I7-F and I8-G) suggest it could hypothetically help in human resources but do not have a clear argument nor genAI tool. One R&D manager thinks again genAI can help:

“I think so too, yes. [...] Once AI is well-trained on the resources you have available, it can make a good suggestion on how to best allocate them for a particular type of project.” Quote 7 – Case 7 – R&D manager

However, based on the pattern of informant’s lack of argumentation what role genAI specifically could have in resource management, in a certain phase of NPD, and the fact that it did not play a role yet, we do not consider there is enough evidence to regard this as a driver in this context.

Second, an *early and sharp product definition* could be enhanced using genAI in the NPD. While no informant has experienced already genAI use enhancing an early and sharp product definition, almost all informants, except one, who does not know whether it could help (I6-E). One informant state that, hypothetically, it will help:

“Very much so. That is also one of the examples I mentioned, they just come up with a... AI can come up with a complete package of a product definition that you might not have thought of yourself.” Quote 8 – I3-C

Moreover, multiple informants (I3-C, I5-D, I7-F, and I8-G) refer to ChatGPT as a (possible) useful tool to improve an early and sharp product definition, since it can translate product requirements but also improvement ideas that enhances the definition. Based on this pattern, we consider this as an applicable driver in the context of genAI use in NPD.

Thirdly, in *customer test*, using genAI could help increase the NPD process speed. All informants did not (yet) experience any advantage in using genAI in customer testing, regarding to NPD speed. In addition, most informants (I2-B, I4-B, I5-D, I7-F, and I8-G) state that it nor hypothetically will help in customer test. However according to an R&D manager (I3-C), it could help since ChatGPT has access to such a large database. Though, as most informants consider customer test as an activity in which genAI cannot be used, mostly because customer tests are seen as something personal, or they simply don't have an example in mind in which it could play a role. Therefore, we don't consider customer test as a driver in this context. As illustrated here:

"No, I really want the end user to experience it themselves, and they need to use it in practice. […] you can't simulate that [..]" Quote 9 – I6-E

Accordingly, we propose:

Propositions 2a, 2b and 2C:

The use of genAI tools in the NPD process (hypothetically) accelerates task execution speed (2a), reduces reliance on external parties (2b) and facilitates an earlier and sharper product definition (2c), which enhances NPD-speed.

Mistakes

Considering the number of mistakes made in the NPD process, no informant could explain current or expected change in number of mistakes after using genAI tools in NPD. They all found it too difficult or impossible to estimate an amount, also in percentage of change. Except two informant (I1-A and I5-D), they all have experience or expectations whether genAI usage leads to an increase or decrease in number of mistakes made in the NPD process. The first returning pattern is that multiple respondents (I3-C, I4-B, I6-E I8-G) suggested that there could (hypothetical) be an increase in NPD mistakes due to the potential errors genAI tools, e.g. ChatGPT (I4-B), are prone to make. However, all informants except two (I1-A and I5D) see multiple reasons why using genAI in the NPD process leads to less mistakes in the whole NPD process. Unfortunately, no specific phases are mentioned, due to both difficulties for informants and insufficient questioning. First, multiple informants (I2-B and I8-G) stated that it could hypothetically lead to less mistakes since ChatGPT makes more consistent and sometimes better software codes. Next to that, one informant (I6-E) indicated that use of ChatGPT hypothetically leads to better knowledge capture through a data bank, which can be used throughout the whole NPD process, leading to less mistakes. Furthermore, several informants (I3-C, I4-B, I7-F and I8-G) stated that using ChatGPT could hypothetically reduce human errors in general, during the whole NPD process, due to helping in (repetitive) work prone for human error:

"He (ChatGPT) is more complete than most engineers, I think. So, in that sense, AI could correct many errors that were unforeseen." Quote 10 – I3-C

Early market test is considered a driver of NPD performance and there are several informants that think that genAI usage in NPD could hypothetically enhance the effectiveness of market tests. The first informant (I1-A) suggested that genAI (ChatGPT and Copilot) could help analyzing data to highlight certain common problems. In case two, one informant (I2-B) stated that genAI might possibly help but that there is not much room for improvement. The other informant (I4-B) explained that ChatGPT could be used giving an example of market analysis in enhancing the effectiveness of market tests. In addition, another informant (I7-F) sees ChatGPT as an opportunity to help structure the market test and gather demographic insights. Conversely, other informants (I5-D, I6-E and I8-G) expressed skepticism or uncertainty about genAI's impact on market testing effectiveness within NPD. Considering mixed responses and a lack of convincing arguments of some informants, we do not assess early market test a driver of NPD performance within this context, as it needs a better understanding and convincing arguments to consider it as a driver within this context.

Accordingly, we propose:

Propositions 3a, 3b, 3c and 3d:

The use of genAI tools in the NPD process (hypothetically) leads to more NPD mistakes, since genAI tools make mistakes (3a). Additionally, the use of genAI tools in the NPD process (hypothetically) leads to enhanced work quality and consistency (3b), better knowledge capture (3c), and less (repetitive) work prone for human error (3d) which lead to less NPD mistakes.

Knowledge sharing

Knowledge sharing was discussed in terms of quality, frequency, and engagement. Informants presented varied, sometimes hypothetical, ideas about the impact of genAI usage on knowledge sharing within the NPD. One informant (I1-A) explained that colleagues tend to visit each other less, leading to less engagement and knowledge sharing. In addition, the informant outlined that their 'knowledge base', based on an GPT-model will enhance knowledge sharing. In case two, an informant (I2-B) also highlighted their 'knowledge base' or 'AI-helpdesk' based on a GPT-model, leading to enhanced knowledge sharing. The informant added that using ChatGPT also leads to increasingly faster document creation. The other informant in this case (I4-B) stated that knowledge sharing decreased in terms of all three aspects:

"I tend to think less (knowledge sharing), because you're more likely to work something out on your own (...) normally departments have to coordinate closely to create something, but if those links don't need to be made so often, because ChatGPT can do in 10 minutes what they would do together do in one day, then knowledge sharing becomes less (..) No, I think knowledge sharing was better when we all had to do it ourselves." Quote 11 – I4-B

Additionally, other informants (I3-C, I5-D and I7-F) (hypothetically) thinks that genAI use leads to less knowledge sharing for the same reasons, indicating a recurring pattern among the informants. Furthermore, in addition to the first two examples (I1-A and I2-B), who are actively testing with an 'knowledge base' powered by GPT-models, other informants (I5-D, I5-E, I7-F and I8-G) suggested the idea of hypothetically increasing knowledge sharing due to increasingly capture knowledge using GenAI tools and enhance the findability of knowledge, for example using some sort of knowledge base, using a GPT-model. Next to that, for the same reasons, informants (I2-B, I4-B, I6-E, I7F and I8-G) explained it could also enhance knowledge sharing to external parties. Therefore, another recurring pattern observed throughout the cases is that genAI usage enhances knowledge capture and findability.

Furthermore, for the 'known driver'; communication and collaboration, informants provide varied perspectives on whether this is a driver of knowledge sharing, in this context. Multiple informants (I2-B, I3-C, I4-B, I5-D and I6-E) are unsure whether genAI usage really impacts communication and collaboration in a positive manner, or even negatively because of colleagues are possibly more likely to work on their own, as indicated earlier. However, three informants (I1-A, I2-B and I7-F) stated ChatGPT and/or CoPilot hypothetically improves documentation and thus communication and collaboration. Further, two informants (I6-E and I-8G) acknowledged genAI's role in facilitating communication and collaboration for information translations. While some informants suggested genAI tools can enhance communication and collaboration, overall, there is a mixed pattern and therefore evidence, that supports this as a driver of NPD knowledge sharing in the context of genAI usage in NPD.

Accordingly, we propose:

Proposition 4a and 4b: The use of genAI tools in the NPD process (hypothetically) leads to enhanced knowledge finding and capture, which improves NPD knowledge sharing (4a). Additionally, the use of genAI tools in the NPD process (hypothetically) leads less personal contact with colleagues, which possibly decreases NPD knowledge sharing (4b).

Performance measure interaction

Based on the informants' responses, it seems evident that there are some interrelationships among the NPD performance measures discussed in this research: cost, speed, mistakes, and knowledge sharing. First, *cost and speed:* two informants (I2-B and I3-C) argue that higher costs lead to more speed, suggesting that greater investment in development accelerates the process. Two other informants (I7-F and I8-G) however, explain that when the project has a smaller budget, it must speed up to compensate. Therefore, this relationship does not necessarily correlate and is context dependent. However, all informants agree that an enhanced speed leads to less cost, due to either efficiency and/or a higher return. However, changes in cost do not always result in changes in speed.

Second, *cost and mistakes:* all cases consistently show that changing costs does not lead to a change in amount of mistakes during NPD. All cases also agree on more mistakes could lead to increased costs due to rework and delays.

Then, *cost and knowledge sharing:* the link between cost and knowledge sharing produced varied responses. Some informants (I2-B, I7-F and I8-G) suggest that changing costs leads to changing knowledge sharing, however, others do not see any link. Furthermore, also changing knowledge sharing and changing cost seem not to link. Some informants (I6-E, I7-F and I8-G), suggest that eventually, better or more knowledge sharing eventually could lead to less cost. However, there is no clear recurring pattern and therefore we see not enough evidence to proof a connection between changing cost and changing knowledge sharing.

Fourth, *speed and mistakes:* there is no consensus among informants that changes in speed leads to changes in mistakes. A few informants (I1-A, I2-B, I5D and I8-G) state that enhanced speed could increases mistakes, or it could be both ways:

"Well, that depends on how you look at it: if you work too quickly, you make more mistakes. However, if you do it more efficiently, you can make fewer mistakes even at a higher speed." Quote 12 – I3-C

Therefore, it depends on the context. All other informants show that enhanced speed can lead to more mistakes. One informant (I1-A) suggests that if you make more and faster mistakes the process speed enhances, as the informant argues that making (not too big) mistakes, leads to more progress. However, a clear pattern among all other cases is that making more mistakes leads to a slower NPD process:

"A mistake often leads to having to go back in your development process, so that slows down the pace" quote 13 – I8-G

Next, *speed and knowledge sharing:* there is consensus among many informants (I1-A, I3-B, I5-D, I6-E, I7F and I8-G) that an enhanced NPD speed decreases knowledge sharing:

"Yes, because sometimes things are rushed, there is often the tendency to forget the handover to other departments." Quote 14 – I1-A

This is a clear example of an enhanced speed decreases knowledge sharing; however, it indicates that it is only the case when NPD speed is too high and does not implicate that faster NPD always leads to more mistakes. Although some informants (I1-A, I4-B, I6-E and I7-F) agree that more knowledge sharing ultimately lead to enhanced speed, all other informants did not see the link, or think it could be also turned around since with more knowledge available, you will search longer. Consequently, we see not enough evidence to proof a connection between speed and knowledge sharing.

Lastly, *mistakes and knowledge sharing:* some informants (I4-B, I6-E and I7-G) explain that more mistakes will lead to more knowledge sharing. However, all other informants did not see a connection, or argued that mistakes in documentation will lead to the sharing false knowledge (I8-G). Furthermore, informants in all cases consistently show that more knowledge sharing will eventually lead to less mistakes, as illustrated here:

"But because we share our knowledge, people are not going to pioneer themselves and thus make mistakes." Quote 15 – I1-A

Accordingly, we propose the following:

Proposition 5a, 5b, 5c and 5d: More NPD speed leads to less NPD cost (5a), more NPD mistakes lead to more NPD cost (5b), more NPD mistakes leads to less NPD speed (5c) and more NPD knowledge sharing leads to less NPD mistakes (5d).

Risks, challenges, and opportunities

Additionally, all informants shared their perspectives on risks, challenges, and opportunities associated with using genAI tools in the NPD, as outlined below:

Risks and challenges

A major concern mentioned frequently are error made by genAI tools, just as outlined previously in the results. One informant (I2-B) noted that ChatGPT still makes numerous mistakes and recognizing when the output is correct can sometimes be challenging. This issue was also highlighted by another informant from that case (I4-B), who stated that you should not thrust too fast on ChatGPT since it makes mistakes. Further, another informant (I8-G) expressed concerns about mistakes due to an improperly trained genAI model (ChatGPT). Furthermore, genAI usage could lead to a decline in human skills, as also explained earlier this chapter. One informant (I5-D) adds that there will likely be less personal communication, whereas another (I4-B) raised concerns, not only about individuals possibly become more isolated but also potentially leading to losing the 'human touch' and declining brand identity. Another major concern is privacy and data security. First, one informant (I3-C) emphasized the risk of sharing information with external parties (such as OpenAI), whereas another (I4-B) noted concern about exposing sensitive company information. Additionally, another (I8-G) expressed less concern about data leaks due to the informants understanding of large language models (such as ChatGPT) operate and the possibility to run such a model on your own server.

Furthermore, using genAI poses several challenges, as multiple informants (I1-A, I3-C and I5-D) pointed out that an integration in the process itself, figuring out when and where to utilize genAI tools and standardizing usage could be a hurdle. One informant (I5-D) suggested using some sort of guidelines should be established for genAI tools usage. Lastly, all informants agreed on the importance of a query/prompt, the input provided to a genAI tool, as this is a major factor for the outcome. They all suggested that using genAI tools more will increase abilities in prompting, however, some informants (I4-B and I6-E) added that some sort of guidelines or instructions could help.

Opportunities

While there are some possible risks and challenges to overcome, informants also explained the biggest opportunities in using genAI in NPD. While some see genAI as an essential tool rather than a team member (I1-A, I2B and I8G, others view it as a supportive colleague (I3-C, I4-B, I5-D, I6-E and I7-F). Despite, most of them agreed genAI tool could enhance speed, cost reduction and knowledge sharing enhancement, as shown previously. Additionally, it can help in more repetitive tasks like coding, also allowing developers to focus on more complex work (I2-B, I5-D and I8-G). Furthermore, there are some genAI tools (such as topology optimization) that support product design in hardware engineering (I1-A, I7-F and D8). lastly, as multiple informants also posed previously, a knowledge repository, using genAI tools to capture and enhance findability is seen as a substantial opportunity.

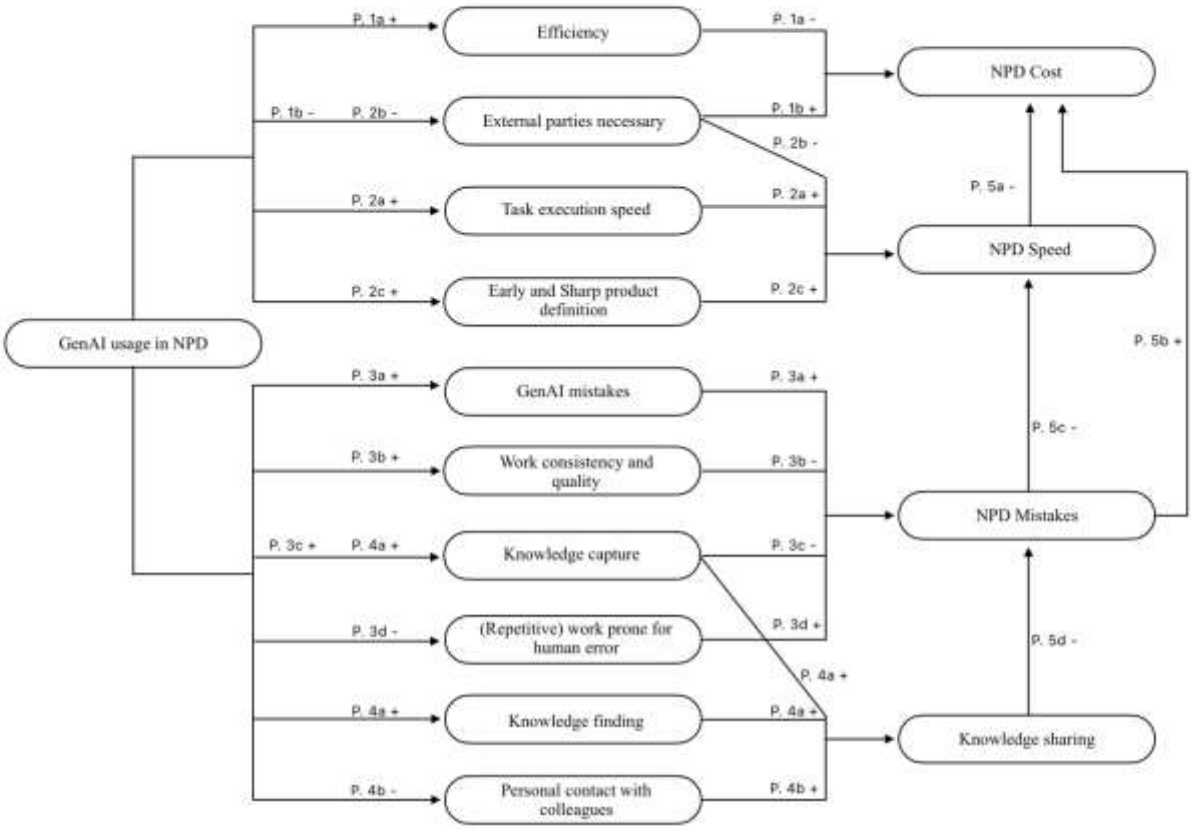

Figure 1: Proposed conceptual model based on (hypothetical) empirical results

Conclusion and discussion

Our exploratory research aimed to provide an understanding of the drivers through which genAI usage in NPD leads to changes in NPD performance and how these NPD performance measures (cost, speed, mistakes, and knowledge sharing) interrelate (*figure 1*).

Additionally, risks, challenges, and opportunities posed by using genAI tools in NPD are provided by the results of our study. Using genAI tools could introduce risks such as errors, over-reliance, a decline in human skills, and privacy concerns. These tools can make mistakes, it can be complicate to recognize these mistakes and using such tools potentially lead to reduces personal communication and isolation. Privacy risks include sharing sensitive information externally, though running models on private servers can mitigate this

Challenges include integrating genAI into processes, standardizing the use, and being able to create an effective prompt/query. By increasingly use such tools, someone can improve prompt/query abilities, and guidelines/instructions may also help. Despite these issues, genAI offers opportunities, as it can enhance speed, reduce cost and mistakes, and improve knowledge sharing. It could be valuable for things including repetitive tasks like coding, product design and could serve as a 'knowledge repository' to enhance information capture and findability.

Theoretical implications

This research contributes to the literature on AI and other digital innovations in NPD (Brock et al., 2020; Rao et al., 1999), in addition it reveals some applications of genAI tools in NPD, contributing to research that previously has been done (Bouschery et al., 2023; Füller et al., 2022). Furthermore, it contributes to literature on AI in NPD and NPD performance (Cooper, 2023b; Zhang et al., 2021). The results of the seven mini cases suggest that genAI usage in general improves three performance measures (cost, speed, and mistakes) posed by Cooper (2023b). However, results also indicate that the use of genAI also could have negative impact on NPD performance. It could negatively introduce a new type of mistakes, since these tools are prone to making mistakes. This increases the amount of mistakes made in NPD, which could result in slower NPD speed and higher NPD cost, as illustrated in *figure 1*.

Additionally, this study suggests that knowledge sharing, as a measure of NPD performance, could be enhanced by using genAI in NPD. It has the potential to improve knowledge capture and findability. However, it proposes that genAI usage might decrease personal contact with colleagues, which potentially reduces knowledge sharing. Therefore, this research contributes to literature about knowledge sharing in NPD (Awwad & Akroush, 2016; Mariani & Dwivedi, 2024).

Managerial implications

From the results, it becomes clear that using genAI tool in the NPD process could be (mostly) beneficial for NPD performance, and through which drivers genAI impacts these NPD performance measures. The use of genAI tools can primarily benefit NPD performance by improving efficiency and enhancing knowledge capture and findability within the organization. By automating certain repetitive tasks such as coding and generating insights from datasets, genAI tools enable teams to allocate time and resources to other, possibly complex, and creative aspects of product development.

Nevertheless, challenges and risk occur in the use of genAI in NPD. One of the primary concerns is data and privacy leaks through genAI tools. Furthermore, the potential for errors in genAI output, which could lead to setbacks in product development implicates a risk. It is essential for NPD teams to create a balance between leveraging genAI's capabilities and making sure that there is human oversight to validate output and keep the personal touch within and out of the company.

To address these risks and challenges, and maximize opportunities, several recommendations can be made. First, encourage a culture of experimentation and continuous learning with genAI tools, to enhance capabilities in prompting/querying and interpreting/validating genAI outputs. GenAI tools make mistakes, so do not always blindly thrust the output; always check and validate it. In addition, explore the possibility to organize 'knowledge-sharing sessions', to educate teams on the workings of models that power genAI tools, prompting/querying, and enhance knowledge sharing on general aspects in NPD, as genAI use could decrease personal contacts. Furthermore, explore a centralized knowledge repository or data base for storing data, ensuring enhanced findability of data across the organisation. Next, emphasize the importance of data security and confidentiality, implementing protocols to protect sensitive information from potential breaches or accidentally being shared with external parties, or using a genAI model on your own server. Moreover, by adopting these recommendations, organizations could more effectively use the power of the genAI tools to drive innovation and competitive advantage in their NPD, while addressing the risks responsibly. Lastly, implementing genAI tools in the NPD process should not be the goal in itself; it should be used when it adds value.

Limitations and directions for future research

Multiple limitations and directions for future research arise from multiple factors within the conceptual framework. First, a limitation is the scope of performance measures considered, in which we focused on the aspects of speed, costs, mistakes and knowledge sharing, while excluding measures such as (perceived) product quality. Therefore, future research could enhance a comprehensive understanding of the impact on genAI use in NPD on more NPD performance measures.

Furthermore, due to the relatively recent adoption of genAI tools by most companies, and some companies do not (yet) use it, respondents often found it challenging to provide exact numbers or percentages, or even estimations of (hypothetical) changes in performance measures, after starting to use genAI tools in NPD. This underscores the need for possibly more longitudinal studies and broader industry adoption to gather more data. However, time constraints also played a role, as this made it necessary to do interviews with informants who had limited or no experience with genAI in NPD, thus potentially less robust results. This is also because (some) informants had to answer questions (partially) on a hypothetical basis. Other informants, whose companies do use genAI tools in NPD, mostly answered questions hybrid; based on both factual experiences and expectations.

Moreover, differences in NPD process and variations in product and industry may influence the outcomes, highlighting the context-specific nature of genAI's impact. Therefore, future research is needed to give a more comprehensive insight in different impact between different industries. T his context dependency also shows that the results are not generalizable to all companies. Additionally, specific phases within the NPD lifecycle in which a genAI tool was used, were not always mentioned by informants, due to difficulties for informants to explain it and probably due to insufficient questioning. Future research should also delve deeper into understanding the impact of using genAI tools in different phases. Lastly, future research is needed to explore drivers more thoroughly.

In conclusion, while this study provides valuable insights into initial impacts of genAI in NPD on NPD performance, considering these limitations and exploring possibilities for future research will contribute to a better understanding.

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Appendix

Appendix A. Interview guide

1. General Information:
    a. What is your role within the company?
    b. How long have you been in this role?
    c. In how many NPD projects have you been involved?

2. NPD Process:
    a. Can you describe how the New Product Development process operates within your company?
        i. Which steps do you use, how ideas are generated, how concept development occurs, testing procedures, commercialization, etc.
        ii. What specific steps are taken during the different phases of the NPD process?
    b. Who is involved in the NPD process within your company? (e.g., departments, roles, external parties, customers)

3. Use of AI in NPD:
    a. In what stages of the NPD process does the company uses Generational Artificial Intelligence, such as ChatGPT and Dall-E.
        i. Does it support decision making or other innovation tasks
        ii. What specific gen AI applications are currently being used in those stages of the NPD process?

4. NPD Performance:

Can you provide specific examples of how the use of gen AI has contributed to improving NPD performance:

a. Does the use of Generative AI in the NPD process lead to changes in NPD cost? If yes: more or less than prior to using gen AI in the NPD process? And how much cheaper or more expensive (in estimated percentage)?
    i. Could you elaborate on these costs?
    ii. How do you think this might come?

iii. How do you think costs could be changed by using generative AI in the NPD process?
1. Do you think managing resources more effectively could help reducing costs?
a. Do you think using gen AI in the NPD process helps doing this?

b. Does the use of Generative AI in the NPD process lead to changes in NPD speed? If yes: faster or slower than prior to using gen AI in the NPD process? And how much faster or slower (in months or weeks)?
i. Could you elaborate on the speed?
ii. How do you think this might come?
1. Do you think managing resources more effectively could help improving speed?
a. Do you think using gen AI in the NPD process helps doing this?
2. Do you think an early and sharp product definition could help improving speed?
a. Do you think using gen AI in the NPD process helps doing this?
3. Do you think customer test of products could help improving speed?
a. Do you think using gen AI in the NPD process helps doing this?

c. Does the use of Generative AI in the NPD process lead to changes in NPD mistakes? If yes: more or less mistakes prior than slower than prior to using gen AI in the NPD process? And how much more or less (in number)?
i. Could you elaborate on these mistakes?
ii. How do you think this might come?
1. Do you think early market tests could help reducing mistakes?
a. Do you think using gen AI in the NPD process helps doing this?

d. Does the use of Generative AI in the NPD process lead to changes in Knowledge sharing? If yes: more or less knowledge sharing than prior to using gen AI in the

NPD process? And how much more or less (in frequency, quality and engagement)?

i. Could you elaborate on knowledge sharing?
ii. How do you think this might come?
    1. Do you think communication and collaboration could help improving the aspects of knowledge sharing?
        a. Do you think using gen AI in the NPD process helps doing this?
iii. Do you think the same about external knowledge sharing?

e. How do you see genAI tools; Hybrid team or tool
f. How do you see the importance of a prompt/query/input?
g. Which aspects of NPD performance do you consider most important for the NPD success of your company?
h. What are or could be the risks or negative sides about using genAI in the NPD process
i. What challenges could occur in using genAI in the NPD process

5. NPD Performance measures interaction:
    a. Cost:
        i. Did/can cost changes lead to changes in speed?
        ii. Did/can cost changes lead to changes in mistakes?
        iii. Did/can cost changes lead to changes in knowledge sharing?
    b. Speed:
        i. Did/can change in speed lead to changes in cost?
        ii. Did/can change in speed lead to changes in mistakes?
        iii. Did/can change in speed to changes in knowledge sharing?
    c. Mistakes:
        i. Did/can number of mistakes change lead to changes in cost?
        ii. Did/can number of mistakes change lead to changes in speed?
        iii. Did/can number of mistakes change lead to changes in knowledge sharing?
    d. Knowledge Sharing:
        i. Did/can knowledge share changes lead to changes in cost?
        ii. Did/can knowledge share changes lead to changes in speed?
        iii. Did/can knowledge share changes leas to changes in mistakes?

Appendix B. Codebook

A. Use of genAI in NPD
    1. No use
    2. Use: examples
B. Cost
    1. No change
    2. Change
        a. Driver(s)
    3. H change
        a. H driver(s)
    4. Managing resources
        a. GenAI helps
C. Speed
    1. No change
    2. Change
        a. Driver(s)
    3. H change
        a. H driver(s)
    4. Managing resources
        a. GenAI helps?
    5. Early and sharp product definition
        a. GenAI helps?
    6. Customer test
        a. GenAI helps?
D. Mistakes
    1. No change
    2. Change
        a. Driver(s)
    3. H change
        a. H driver(s)
    4. Early market test
        a. GenAI helps?
E. Knowledge Sharing internal

1. No change
2. Change
    a. Driver(s)
3. H change
    a. H driver(s)
4. Communication and collaboration
    a. GenAI helps?

f. Knowledge Sharing external
    1. No change
    2. Change
        a. Driver(s)
    3. H change
        a. H driver(s)

g. Additional
    1. Hybrid team - tool
    2. Query/prompt
    3. Most important performance measures
    4. Risks
    5. Challenges
    6. Biggest opportunities

h. Interaction Performance measures
    1. Cost - speed
        a. Cost → Speed ++
        b. Cost → Speed +-
    2. Cost - mistakes
        a. Cost → mistakes ++
        b. Cost → mistakes +-
        c. Don't know/no/not always
    3. Cost – knowledge sharing
        a. Cost → knowledge sharing ++
        b. Cost → knowledge sharing +-
        c. Don't know/no/not always
    4. Speed - cost
        a. Speed → Cost ++

    b. Speed → Cost +-
    c. Don't know/no/not always
5. Speed - mistakes
    a. Speed → mistakes ++
    b. Speed → mistakes +-
    c. Don't know/no/not always
6. Speed – knowledge sharing
    a. Speed → knowledge sharing ++
    b. Speed → knowledge sharing +-
    c. Don't know/no/not always
7. Mistakes - cost
    a. Mistakes → Cost ++
    b. Mistakes → Cost +-
    c. Don't know/no/not always
8. Mistakes - speed
    a. Mistakes → Speed ++
    b. Mistakes → Speed +-
    c. Don't know/no/not always
9. Mistakes – knowledge sharing
    a. Mistakes → knowledge sharing ++
    b. Mistakes → knowledge sharing +-
    c. Don't know/no/not always
10. Knowledge sharing - cost
    a. Knowledge sharing → Cost ++
    b. Knowledge sharing → Cost +-
    c. Don't know/no/not always
11. Knowledge sharing - speed
    a. Knowledge sharing → Speed ++
    b. Knowledge sharing → Speed +-
    c. Don't know/no/not always
12. Knowledge sharing - mistakes
    a. Knowledge sharing → mistakes ++
    b. Knowledge sharing → mistakes +-
    c. Don't know/no/not always