AI Adoption in the Business Model and its impact on Firm Performance for High-tech and Low-tech Organizations

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A firm's business model is a framework or a plan that outlines how the firm creates, delivers, and captures value (Snihur & Markman, 2023). This includes their value proposition, target market, revenue streams, cost structure, distribution channels, resources, and partners. Business model innovation encompass changes to these elements of the business model or the architecture linking these elements (Foss & Saebi, 2016). One of the drivers of business model innovation is technological development as it can create new ways of creating and delivering value (Sorescu et al., 2011; Padgett & Mulvey, 2007). Artificial intelligence is a recent technological development which drives business model innovation as it is able to reshape different parts of the business model like the value proposition, resources, relationships and so on (Sidaoui et al., 2020; M. Huang & Rust, 2020; Puntoni et al., 2020). We know that AI is increasingly being adopted by firms, and this is expected to increase even further in the next years (Lee et al., 2022). However, there is limited understanding of the relationship between adopting AI in the business model and firm performance. Some studies researched this relationship and found a positive effect, but they primarily focused on High-tech firms (Lee et al., 2022; Mikalef & Gupta, 2021; Baabdullah 2024).

Different types of organizations have different types of business models and because of this, disruptive innovations like AI potentially have different impacts on those organizations (Law et al., 2021). High-tech organizations are characterized by high levels of technological complexity, high R&D investments and are used to dealing with innovations while low-tech organizations have opposite characteristics and have weaker innovative capabilities (Pavitt, 1984). The study of Lee et al. (2022) found that organizations would only benefit from AI adoption when also investing in R&D and other complementary technologies. This aligns well with high-tech organizations as they already invest heavily in R&D and have high technological complexity levels in the business model. The only study that researched AI adoption for low-tech organizations is the study of Liu et al. (2020). The authors found that AI adoption increased innovation performance in low-tech organizations because knowledge creation is very easy as the technology threshold is low. The findings of this article are controversial to the findings of Lee et al. (2022) as they state organizations only benefit from AI when investing in other technologies and have high R&D investments. There is a lack of clear understanding of the influence of AI adoption in the business model on firm performance when moderating for high- and low-tech organizations. This limits the ability of decision makers to make the right decision which is problematic as AI adoption is growing and becoming available to more organizations as computing costs are declining (Lee et al., 2022; Huang & Rust, 2020).

To gain understanding of this relationship this study focusses on the relationship between AI adoption in the business model and firm performance while moderating for high- and low-tech

organizations. Quantitative methods are used to test the proposed hypotheses and answer the research question. Data is collected by means of a survey that is sent to 1300 randomly selected Dutch SME's. The analysis starts with multiple regression analysis to interpret the main effect of AI adoption on firm performance. Then moderation analysis is performed in SPSS using the PROCESS macro extension. This interprets the moderation effect of high- and low-tech on the main effect of AI adoption on firm performance. With understanding of the main effect and the moderation effect this study enriches the literature by studying the relation between AI adoption and firm performance in a different context than other studies (Lee et al., 2022; Mikalef & Gupta, 2021). It also enriches the literature by interpreting the moderation effect of high- and low-tech on the main effects which, to the best of my knowledge, no other study has done. With this study the following research question is answered: *"What is the effect of AI adoption in the business model on firm performance and does this relationship differ for high- and low-tech organizations?"*

This study has practical implications as well as contribute to the literature on business model innovation and artificial intelligence. It gains understanding of the relationship between AI adoption and firm performance and if this relationship is different for high- and low-tech firms. An extensive literature review is conducted and there is limited literature available, especially in top ranked journals, on this relationship. The articles that have studied this relation are primarily focused on high-tech firms. This research gains understanding of this relation, plus differentiate between high- and low-tech firms thereby enriching the literature. This study also has practical implications as understanding of this relationship will help decision makers and investors to decide on incorporating AI in their business model.

Based on the analysis of 74 Dutch SME's, this study did not find support for the proposed hypothesis. Higher levels of AI adoption in the business model do not lead to significantly higher levels of firm performance. The findings of this study contradict prior research, which predominately suggest there is a positive relationship between AI adoption and firm performance. Despite theoretical expectations that high-tech organizations would benefit more from the adoption of AI than low-tech organizations, there was no significant difference found between these two types of organizations. This study contributes to the Resource-Based View and literature on business model innovation. This study highlights that AI technology on itself does not automatically enhance firm performance. Potential contextual factors, complementary investments and proper integration could be important influencers to determine the success of AI adoption. Future research should emphasize these factors and examine which contextual and internal factors determine the success of AI adoption in the business model.

Theoretical Framework

The Business Model

Understanding of the business model is an important starting point for this research. There is no commonly accepted definition of a business model, but it can be described as the way firms create, capture, and deliver value for their customers (Snihur & Markman, 2023). The business model of a firm may outline how it creates value for their customers via their key activities and pricing mechanism, how the firm designed their governance structure to reduce costs and how they generate revenue (Sorescu et al., 2011). The way a firm designs its business model is positively related to firm performance when it creates value and does not decrease bargaining power relative to stakeholders (Zott & Amit, 2007). The relationship of business model design and firm performance is moderated by the market and competitive environment (Sorescu et al., 2011). The authors from the article of McArthur & Nystrom (1991) also found support for the influence of external factors on the relationship between the business model and firm performance. This shows the importance of matching the business model to the environment to maintain or gain a competitive advantage.

Business Model Innovation

Business model innovation can be described as follows: *"designed, novel, nontrivial change to key elements of a firms business model and/or the architecture linking these elements"* (Foss & Saebi, 2016, p. 201). According to Snihur & Markman (2023) Business model development is the process where the organization develops a business model that is new to the world, new to the market or new to the firm. Business model innovation can create new ways to create, capture and deliver value and can apart of economic performance also enhance responsibility and sustainability (Snihur & Markman, 2023; Casadesus-Masanell & Zhu, 2012). These changes in the business model encompass adding novel activities, linking activities in novel ways and/or by changing one or more parties that perform the activity (Amit & Zott, 2012). The new business model should enable organization to maintain or gain competitive advantages in response to the previously talked about changing environment (Menter et al., 2022). According to Najafi-Tavani et al. (2023) there are two types of business model innovation: novelty-centered- and efficiency-centered business model innovation. The first one leads to differentiation advantages while the second one leads to cost advantages, both leading to increased performance. An important finding from Menter et al. (2022) is that incremental changes to the business model enhance person-organization fit and radical changes decrease person-organization fit.

Multiple factors drive business model innovation, these drivers could be internal as well as external (Sorescu et al., 2011). A potential internal driver could be a strong customer orientation of the organization as a focus on improving customer experience prompts organizations to come up with innovative ways to align their business model with the customer (Zomerdijk & Voss, 2009). The

composition of the TMT also seems to have an influence on business model innovation. Cognitive and ideological diversity within the TMT increases attention-scope and business model innovation intensity which positively effects business model innovation. This relationship is moderated by longevity, suggesting the relationship between diversity and business model innovation increases as TMT members longer work together (Narayan et al., 2020). A general emphasis on innovation could also lead to Business model innovation through experimentation (McGrath, 2010; Chesbrough, 2010). External forces also drive business model innovation. As values of customers change, organizations need to adapt to keep creating value for their customer which in turn creates value for the firm (McGrath, 2010). Technological developments drive business model innovation as it enables firms to recreate their activities to deliver and create more value (Padgett & Mulvey, 2007). The emergence of the internet for example created numerous successful business models based on electronic platforms (Mahajan et al., 2002).

As every organizational change process business model innovation encounters several barriers. These barriers prevent the organization from successfully developing and implementing the new model but also to identify opportunities to create a new successful model. The article of Gilbert (2005) delves into the structure of inertia, which is a dominant barrier for organizational change. The author makes a distinction between two sources of inertia: resource rigidity and routine rigidity. Resource rigidity refers to the failure to change investment patters and routine rigidity refers to the failure to change processes that utilize those resources. Sorescu et al. (2011) also identified inertia and resource commitment as barriers for business model innovation as well as cognitive factors and the success of the current business model. The high investment needed to research and to develop a new business model and the risk of failure are also factors that prevent organizations to innovate their business model (Amit & Zott, 2001).

So how could organizations successfully innovate their business models? Sorescu et al. (2011) explains that the new business model should not be easy to imitate by competitors for the business model to be sustainable. She also emphasizes organizations to continuously look for new business models: "*start thinking about the next business model innovation as soon as the current one is implemented"* (Sorescu et al., 2011, p. 14). Achtenhagen et al. (2013) identifies three key capabilities to renew and adapt their business model. The first capability is to act highly entrepreneurial and experiment with new business models. The second capability is to use resources in a balanced way for controlled expansion. The last capability is to achieve a coherence between culture, leadership, and employee commitment.

The innovation of a firm's business model is found to positively influence firm performance (Zott & Amit, 2007). Besides of improving economic performance and reduces economic risk and uncertainty it also enhances sustainability and responsibility as new business models can help to

solve societal issues (Markman et al., 2016; Snihur & Markman, 2023). The strength of the relationship between business model innovation and firm performance differs as not every organization benefits equally from business model innovation. National contingencies and the maturity of a firm moderate this relationship. Ilyas et al. (2023) found that high levels of masculinity and individualism leads to a weaker link and high levels of customer orientation, economic freedom and education leads to a stronger link. Other findings of this study were that start-ups seemed to benefit more of business model innovation than mature firms. The study of Leppänen et al. (2023) found that novel business models alone do not lead to improved performance but and it needs complementary value drivers as well. When combined with efficiency and strategies, in particular differentiation, it leads to high performance.

Artificial Intelligence

In the past years artificial intelligence has made a disruptive advance and innovations regarding application and development are rapidly expanding (Lee et al., 2022). Artificial intelligence can be conceptualized as follows: "*The use of computational machinery to emulate capabilities inherent in humans, such as doing physical or mechanical tasks, thinking, and feeling*" (Huang & Rust, 2020, p.30). According to that same article the most disruptive aspect of AI is that it replaces and improves upon human thinking. In the marketing industry for example, thinking and feeling intelligence are the primary requirements and technology to assist in these processes was very limited available. With AI's rapid developments it is able to help with the thinking tasks and will eventually assume the feeling tasks as well. AI is seen as the development of the generation and set to reshape the business environment just as automation did for manufacturing workers (Loebbecke & Picot, 2015). Experts are not sure how AI will exactly shape the business environment, the article of Huang & Rust (2020) states it is able to replace human thinking while Pakarinen & Huising (2023) concluded that it will become part of the network of interactions in creating human expertise.

Artificial intelligence has the potential to change many aspects of organizations including decision making, process optimization and problem solving (Bailey et al., 2022). Natural language processing (NLP) is one of the main functions of AI which employs computational techniques for learning, understanding, and producing human language (Hirschberg & Manning, 2015). This function can be used to analyze, summarize, and offer insight into large amounts of data. Computer vision (CV) is able to analyze visual data like images and videos and detect, understand, and segment this data (Hussain, 2023). Machine learning (ML) is another subset of AI that enables systems to learn and improve their performance. It is able to classify data and based on the data predict outcomes and provide recommendations (Von Krogh et al., 2023).

Influence of AI on business model innovation

AI can change different components of the business model of an organization. Incorporating the technology could require new resources and partnerships with providers of the technology and databases or expert partners in this area of technology. It can change the relation between the consumer and the organizations by using chatbots to interact with consumers (Sidaoui et al., 2020). It can also be used to standardize routine and transactional tasks thereby changing activities and improving the cost structure (M. Huang & Rust, 2020). AI offers solutions that companies deliver to consumers like self-driving cars or SIRI on an iPhone and thereby changing the value proposition and revenue streams of organizations (Puntoni et al., 2020). So, with its diverse application AI can change many different aspects of the business model of organizations.

AI is increasingly being adopted by organizations and this is expected to further increase in the next years (Lee et al., 2022). Incorporating AI can be a challenging process for organizations. This is because it entails acquiring new knowledge, resources and the business model of the organizations should be innovated to fit with AI (Haefner et al., 2021). According to this article there is also an influence of AI on business model innovation as business models need to be reshaped to fit with the new technology. Mariani & Nambisan (2021) found that the use and implementation of AI can help firms to identify and prioritize consumer demand and determine the market potential in the research stage of new business models. Mariani et al. (2023) formulates multiple drivers for AI adoption. The first one is an economic driver where firms adopt AI to try and reduce costs or increase productivity. The second driver is a technological driver as big data and IoT drive adoption of AI. The last one is a social driver when firms adopt AI to try and enhance sustainability or improve waste management.

There is limited generalizable literature available, especially in the top ranked journals, about the performance implications of AI adoption in the business model. The article of Mikalef & Gupta (2021) found that AI capability positively influences creativity and performance. This study however only used data of firms from the United States and mostly consisted of high-tech companies. Besides, the main focus of the article was to examine the resources needed to create AI capability. The successful adoption of AI can enhance efficiency of decision makers as found by Baabdullah (2024). The article of Lee et al. (2022) also found a positive link between AI adoption and performance. They found AI adoption only had a positive influence on firm performance when adoption levels were high. This study and the study of Baabdullah (2024) also only focused on high-tech organizations. As there are some articles that found a positive influence of AI adoption in the firm's business model these all focused on high-tech organizations.

There is limited understanding of the performance implications of AI adoption in low-tech organizations. Studying this relationship could be interesting as innovation activities and innovation performance are different in high-tech and low-tech organizations (Law et al., 2021). High-tech organizations have higher technological complexity levels, extensive R&D activities and are

characterized by product innovations. On the other hand, low-tech organizations are characterized by lower R&D investments, weaker internal innovative capabilities and are dependent on knowledge acquisition (Pavitt, 1984). Innovations in low-tech organizations mostly comes from accumulated practical experience and specialization (Nelson & Winter, 1977). Low-tech firms usually lack the absorptive capacity due to low R&D investments to take advantage of external knowledge for product innovation (Flor et al., 2021). The differences between high-tech and low-tech firms are also highlighted in the paper of Kearney et al. (2019). The lack of knowledge about the relationship of AI adoption on firm performance in low-tech firms is concerning as low-tech firms represent more than twice the share of manufacturing than high-tech firms (Kearney et al., 2019).

The only article that was found to study AI adoption in low-tech organizations is the article of (Liu et al., 2020). This study concludes that the higher levels of AI in an organization leads to higher levels of technological innovation through knowledge creation, knowledge spillover, learning ability and investments in R&D. They found that this relationship was stronger in low-tech firms as technological level and technical threshold in these organizations are lower making knowledge creation easier. This study is also very location specific as it only focused on the Chinese manufacturing industry. Also, this study focused on technological innovation as an outcome of AI adoption leaving the question whether it influenced the financial performance of the organizations.

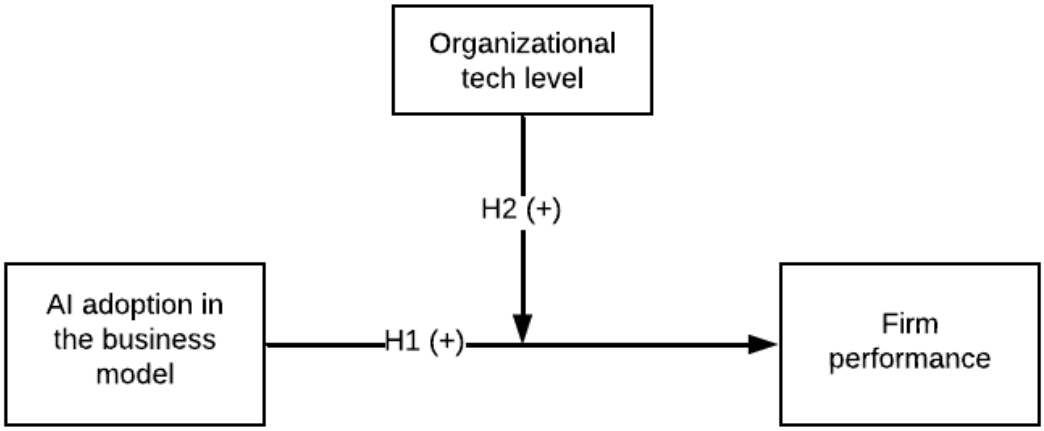
This 'gap' in the literature creates an interesting field to study as it is unclear whether the adoption of AI in the business model will lead to an increase in firm performance when moderating for high-tech and low-tech organizations. Mariani et al. (2023) also suggests further research to study whether high levels of AI adoption and low levels AI adoption leads to different economic outcomes compared to low levels of adoption. Understanding the performance implications of AI adoption is important for several reasons. Firstly, as AI technologies are increasingly being adopted and further developed, as supposed by Lee et al. (2022), more businesses will face the decision to incorporate AI in their business model. As the innovation of business models requires high investments it is vital for decision makers and investors to make the right decision (Amit & Zott, 2001). Secondly, finding the performance implications of the adoption of AI in the business model in high- and low-tech firms will fill in the literature gap and advance empirical knowledge, enriching the literature on business model innovation and technological disruption.

Hypotheses development

Based on the literature the following conceptual model is hypothesized in this chapter.

Figure 1

Conceptual Model



Note. This figure demonstrates the conceptual model of this study. 'H1' represents hypotheses 1 and 'H2' represents hypotheses 2. The '(+)' indicates a positive relation.

The first hypothesis regards the main effect between AI adoption in the business model and firm performance. According to the studies of Mikalef & Gupta (2021) and Lee et al. (2022) higher levels of AI adoption in the business model would lead to higher firm performance. The study of Lee et al. (2022) found that the adoption of AI in the business model only leads to more firm performance when adoption levels were high as it helps organizations with liberating routine tasks, reducing human error and biases and help discover new business opportunities. Mikalef & Gupta (2021) also found that organizations that have the capability to leverage its AI resources perform better as it increases their creativity and overall performance. Successful adoption of AI also enhances efficiency of decision makers thereby contributing to the functional performance of an organization (Baabdullah, 2024).

Low levels of AI adoption in the business model would not yield significant performance improvements as suggested by Lee et al. (2022). Firms need to adjust to implement AI and reorganize their practices effectively around the new technology. This is also found in the article of Haefner et al. (2021) where they also highlight that this process of adjusting and acquiring the right knowledge is challenging. Also, to fully leverage the potential of AI organizations need to make complementary investments in R&D, data infrastructure, cloud computing and AI-specific human capital (Lee et al., 2022). Only when these prerequisites are met by the organization it will start to experience

performance improvements. The following hypotheses is formulated about the main effect of AI adoption in the business model on firm performance:

H1: AI adoption in the business model positively effects firm performance.

High-tech organizations are considerably different from low-tech organizations which influences how and where these organizations innovate (Law et al., 2021; Nelson & Winter, 1977). The articles that have studied the relationship between AI adoption and firm performance are primarily focused on high-tech organizations. Because of the differences between high- and low-tech firms the relationship between AI adoption in the business model and firm performance could be different for these organizations. Therefore, this research will use 'organizational tech level' as a moderator variable to study if the relationship between AI adoption in the business model and firm performance differs for high- and low-tech organizations.

The studies that researched the relationship between AI adoption and firm performance are primarily focused on high-tech organizations. They found that only high levels of AI adoption in the business model increased firm performance for high-tech organizations (Lee et al., 2022; Mikalef & Gupta, 2021). An important finding of the study that Lee et al. (2022) did was that the adoption of AI in the business model would only lead to improved performance when the organization also makes complementary investments in amongst other R&D. This aligns well with high-tech organizations because they often already invest heavily in R&D. According to Pavitt (1984) the business models of high-tech organizations have higher technological complexity levels which can make the organizations more suitable for implementing AI technologies than that of low-tech organizations. Therefore, I hypothesize that high levels of AI adoption in the business model positively influence firm performance for high-tech organizations. On the other hand, low levels of AI adoption would not result in an increase in firm performance for high-tech organizations due to the lack of complementary investments.

With AI's growing applications and declining computing costs the technology becomes available for a wider range of firms, including low tech firms (Huang & Rust, 2020). The performance implications of the adoption of AI in the business model for low-tech organizations however is largely understudied and controversial. In the article of Liu et al. (2020) the authors found a positive link between levels of AI adoption and innovation performance in low-tech firms within the Chinese manufacturing market. They state that this relationship is stronger in low-tech firms because its technology levels are low making knowledge creation very easy with the adoption of AI. Although the study of Liu et al. (2020) focused on innovation performance which is a different performance implication than this study uses it does show support for low-tech organizations benefitting from AI.

This does not align with the study of Lee et al. (2022) because they conclude organizations can only benefit from AI when making investments in R&D and complementary technologies while low-tech organizations are characterized by low R&D investments and low technology levels (Pavitt, 1984). Therefore, low-tech organizations would not benefit as much from incorporating AI technologies in their business model as high-tech organizations would.

The study of Liu et al. (2020) leads me to believe that low-tech organizations can already benefit from low levels of AI adoption without the need to make a lot of complementary investments. As adoption levels of AI increases the need for complementary investments also increases and that could be where the performance implications dissolve for low-tech organizations as they are not suitable to make these kind of investments (Law et al., 2021). That would mean that the direction of the relationship between AI adoption in the business model and firm performance is negative for low-tech organizations. The following hypotheses is formulated regarding the moderation effect of organizational tech level on the main effect of AI adoption in the business model on firm performance:

H2: The relationship between AI adoption in the business model and firm performance is positively moderated by the organizational tech level of the organization.

Methodology

Research Setting

This study used a quantitative research method to empirically test the proposed hypotheses. Quantitative analysis is best suited for this study as a larger sample of organizations is analyzed and it allows for statistical validation of the relationship between AI adoption and firm performance and the moderation effect on this relation. A random list of 1300 Dutch SME's was subtracted from the Orbis database to ensure minimal bias in the selection of organizations in the sample. Due to feasibility reasons this study only focused on Dutch organizations. Public and non-profit organizations are not included in the sample to ensure the study focuses on organizations that are profit driven and adopt AI technologies to enhance performance. Organizations with less than 20 employees are also excluded from the sample to guarantee minimum firm complexity (Şimşek et al., 2005; Soto-Acosta et al., 2018).

Data Collection

Data is gathered by means of a survey. The survey measures AI adoption, firm performance and organizational tech-level as will be explained in a later subchapter. In appendix A the questions of the survey are outlined. To minimize confusion each of the concepts will be clearly explained to the

respondents when sending the survey. The surveys also consist of the right questions to measure the control variables. The survey was sent to a total of 1300 companies via email and posted on LinkedIn.

Measurements

AI Adoption

The measurements of AI adoption used in this study are the same measurements as the authors used in the study of Lee et al. (2022). Respondents are asked to rate their AI adoption on three AI technologies: 1) natural language processing, 2) computer vision and 3) machine learning. The adoption rates will be measured by asking the respondents to rate their adoption of the three technologies accordingly: 1 = no adoption, 2 = testing stage, 3 = 0%-5%, 4 = 5%-25%, 5 = 25%-50%, 6 = 50% or more. As organizations often use the AI technologies in conjunction this study takes the highest adoption rate of one of the three technologies. The adoption percentages represent the use of AI in organizational activities. An adoption rate of 25% means that the organization uses AI in 25% of the organizational activities.

Firm Performance

Firm performance is measured by relative revenue growth in percentages per year which Lee et al. (2022) also uses. The focus of this study is on SMEs of which a lot are not publicly listed and so do not publicly report financial results. Getting insights in detailed financial results could potentially form an obstacle so therefore the decision is made to measure firm performance by means of relative revenue growth in percentages per year.

High-Tech and Low-tech Organization

To determine whether an organization is High-tech or Low-tech this study used the same measurements as in the study of Law et al. (2021) which they obtained from the Frascati Manual (Frascati Manual, 2002). They define organizations that have an annual R&D intensity of 5% or higher as high-tech organizations and organizations that have an annual R%D lower than 5% as non-high-tech or low-tech organizations. R&D intensity means the percentage of the revenue an organization annually invests in R&D.

Analytical Approach

The conceptual model exists of five independent variables (AI adoption in the business model and four control variables), one dependent variable (firm performance) and the moderation variable of ‘organizational tech level’. Because we have 5 dependent variables (including 4 control variables) and one independent variable multiple regression analysis is the most suitable method to analyze the hypotheses (Hair et al., 2019, p. 266; Blazevic, 2023). The analysis started by conducting a multiple regression analysis in SPSS with AI adoption, control variables and firm performance to analyze the main effect. After analyzing the main effect, moderation analysis is performed using the PROCESS

macro extension in SPSS. The moderation analysis will interpret the moderation effect of high-tech and low-tech on the main effect.

Control Variables

Different control variables are included in the analysis to isolate the relationship between the independent and the dependent variable as much as possible. The first control variable is firm age as firm age potentially influences firm performance (Dang et al., 2021). In comparable studies they also controlled for firm size, current business model and company valuation so in this study these are also used as control variables (Lee et al. 2022). It would be possible to include more control variables but due to feasibility reasons the decision is made to limit the control variables to this number.

Firm size is measured on a scale corresponding to 0-20 employees, 20-50 employees, 50-100 employees, 100-150 employees, 150-200 employees and 200-250 employees. Firm age is measured by a scale corresponding to 0-10 years, 10-20 years, 20-30 years, 30-40 years, 40-50 years and 50+ years. Current business model is measured by business to business, business to consumer and business to government. Company valuation is measured corresponding to 0-0.5 million, 0.5-1 million, 1-2 million, 2-5 million, 5-10 million and 10+ million.

Ethical Considerations

This study adheres to the Dutch code of conduct for research integrity. This means I conducted this research while following the following principles: honesty, scrupulousness, transparency, independence, and responsibility (Dutch research counsel, 2018). Besides these principles from the Dutch code of conduct I prioritized respect for all parties involved. The participants in this study have been clearly informed about the purpose of the research and their data is only used with consent. Gathered data is anonymized ensuring confidentiality and anonymity for the participants data.

Results

Missing Data

The extend of and the processes leading to missing data will be assessed in order to determine the best course of action to handle the missing data (Hair et al., 2019). The reason for missing data is caused by the respondents refusal to answer to any of the survey questions and therefore the missing data is not ignorable (Hair et al., 2019). The extend of the missing data is less than 10% as shown in Table 1, which makes the cases acceptable to any imputation method according to Hair et al. (2019). Mean substitution is used to replace the missing values for the mean value of that variable.

Table 1

Missing values

Variable	N	Missing	
		Count	Percent
Company size	74	0	.0
Company age	74	0	.0
Business model	74	0	.0
Company valuation	73	1	1.4
R&D investment	72	2	2.7
NLP adoption	74	0	.0
CV adoption	74	0	.0
ML adoption	74	0	.0
Firm performance	72	2	2.7
Firm performance.0	73	1	1.4

Data Preparation

Before starting the analysis some variables need to be changed in order to make them appropriate for the analysis. A new variable 'AI adoption' is computed by taking the maximum value of variables 'NLP adoption', 'CV adoption' and 'ML adoption'. As explained in a previous chapter these AI technologies are often used in conjunction of each other so the maximum value of one of the three variables represents the amount of AI adoption in the business model (Lee et al., 2022). Another new variable 'Revenue growth' has been computed by taking the average of the variables 'Firm performance' and 'Firm performance.0', which represents respectively the revenue growth of the last fiscal year and the projected revenue growth of the current fiscal years. The averages of these variables are rounded up as these variables are measured in a mutually exclusive scale meaning decimals do not hold any value.

Regression analysis requires variables of interval measurements, for variables that do not meet that requirements dummy variables are created (Hair et al., 2019). The variable 'Business model' is of ordinal measurement level and for this variable dummy variables have been created. The moderator variable is a dichotomous variables with the two categories 'less than 5%' and '5% or more' representing the organization being 'low-tech' or 'high tech'. all other variables are measured on either a five- or six-point scale so you can argue that these variables are not of interval

measurement. The decision has been made to incorporate these variables in the analysis and treat them as interval variables. This has been considered when interpreting the results.

Descriptives

The sample consists of 74 participants, all Dutch SME's. In Table 2 the descriptive statistics and correlations are presented. 'Company size' has a mean value of 2.18 and a median of 2.00 which corresponds to the category 50-100 employees. Most companies in the data set are between 30 and 40 years old as the median of 4.00 corresponds to this category. The majority of the sample (81.1%) consists of companies with a B2B business model. The median for 'Company valuation' is 6.00 corresponding to a valuation of €10 million or above. The mean however is closer to 5 which corresponds to a valuation of €5 to €10 million. 48 companies in the sample have an annual R&D investment less than 5%, meaning they belong to the category of 'low-tech' organizations. 24 companies are 'high-tech' companies with an annual R&D investment of 5% or higher. The adoption of NLP technology has a mean of 2.58 and a median of 2, meaning most of the companies in the dataset are in the testing stage of incorporating NLP technology. The same goes for computer vision technology but the mean for this variable is slightly lower with 2.05. Machine learning technology is less common in the data set with 42 companies having no adoption of the technology. The mean however is almost the same as for computer vision technology indicating that the companies that use machine learning technology have relatively high adoption levels. The revenue growth of the current year (Firm performance) and the upcoming year (Firm performance.0) are relatively close with most companies indicating a 5%-10% revenue growth. The mean for last year's revenue growth is slightly higher than for the upcoming year.

Table 2

Descriptive Statistics and Correlations

Variable	N	Mean	S. D.	1	2	3	4	5	6	7	8
1. Company size	74	2,18	1,232	--							
2. Company age	74	4,08	1,781	.306**	--						
3. Company valuation	74	5,12	1,110	.354**	.432**	--					
4. B2B	74	0,8108	0,39433	.013	.120	.211	--				
5. B2C	74	0,1351	0,34420	.008	-.063	.080	-.818**	--			
6. B2G	74	0,0541	0,22767	-.034	-.112	-.244*	-.495**	-.094	--		
7. AI adoption	74	2,9189	1,48745	-.074	-.266*	-.061	.114	-.139	.013	--	
8. Revenue growth	74	3,1351	1,18581	.101	-.349**	-.087	.026	-.112	.124	.301**	--

Note. Coefficients are reported; ** p < .01, * p < .05; Significance is based on two-tailed tests.

Assumptions for Regression analysis

Normality

The variables in the dataset need to meet several assumptions for the analysis to be valid. Because of the small sample size used in this research the variables need to be normally distributed in order to perform significance tests (Field, 2017 p.388). If a variable deviates from normality all statistical tests are invalid (Hair et al., 2019). The variables have been assessed for normality by looking at the Skewness and the Kurtosis which may not have a value smaller than -3 or greater than 3 (P. Ligthart, personal communication, July 3, 2024). The values for the Skewness and Kurtosis for all variables are between -3 and 3 conforming the variables are normally distributed and meet the assumption of linearity.

Table 3

Skewness and Kurtosis

	Company size	Company age	Company valuation	AI adoption BM	Revenue growth
Mean	2.18	4.08	5.12	29.189	31.351
Median	2.00	4.00	6.00	30.000	30.000
Skewness	1.012	-.275	-.993	.579	.643
Std. Error of Skewness	.279	.279	.279	.279	.279
Kurtosis	.274	-1.396	-.201	-.516	.149
Std. Error of Kurtosis	.552	.552	.552	.552	.552

Linearity

For regression analysis the independent variables should have a linear relation with the dependent variable (Hair et al., 2019). 'AI adoption' and 'Company age' meet this assumption. For the variable 'Business model' dummy's were made which automatically meet the assumption of linearity. 'Company size' and 'Company valuation' show a non-linear relationship with the dependent variable. Normally these variables can be transformed to meet the linearity assumption, but this did not have the desired outcome. After consulting with my supervisor, I have decided to leave these variables in the analysis as they are control variables and not the focus of the model.

Multicollinearity

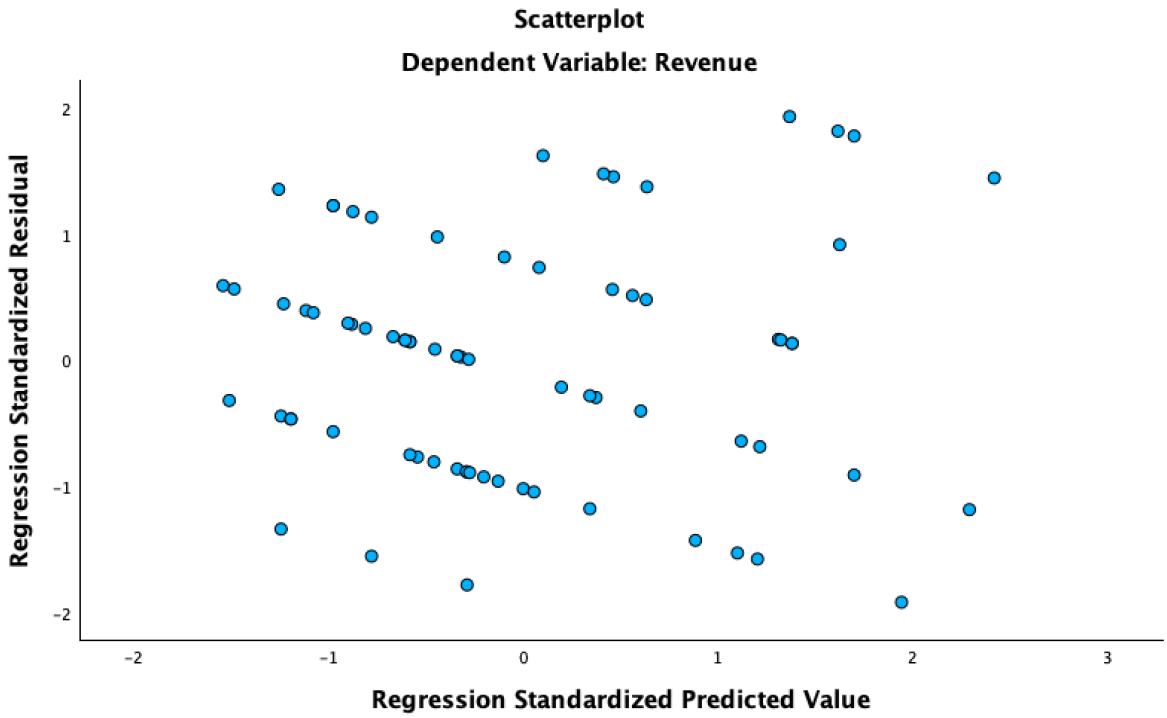
For regression analysis the independent variables should not correlate too much with each other. The maximum correlation between the independent variables may therefore not exceed a value of .70. Looking at the Correlation in Table 2 the variables B2B and B2C highly correlate with each other. SPSS automatically removes the variable B2B from further analysis. After removing this variable, the multicollinearity assumption is met.

Homoscedasticity

The last assumption of regression analysis is homoscedasticity which refers to the assumption that the dependent variable exhibits equal levels of variance across the range of independent variables (Hair et al., 2019). To assess homoscedasticity, I looked at the scatterplot with the regression standardized predicted values on the x-axis and regression standardize coefficients on the y-axis. The scatterplot shows a random pattern which indicates this meets the assumption of homoscedasticity. This is confirmed by assessing the standardized residuals as there are no values exceeding -3 and 3.

Table 4

Scatterplot



Hypotheses Testing

As all the assumptions for multiple regression analysis have been met the regression model is estimated and the predictive accuracy of the independent variables is assessed (Hair et al., 2019). The independent variables in the model reliably predict the dependent variable F= 2.628, p .024. The adjusted R square is .118 which according to Field (2017) corresponds to an explanatory power between medium and high but closer to medium than high. Hypothesis 1 argues that higher levels of AI adoption in the business model leads to higher levels of firm performance. In Table 3 the effects of the independent variables on the dependent variables are presented. The main effect of AI adoption

in the business model on the dependent variable firm performance is not significant with a p value of .079 thereby failing to support hypothesis 1.

Table 3

Regression Results

Variables	Model 1	Model 2
Control variables		
Company size	-.013	-.013
Company age	-.255**	-.214*
Company valuation	.103	.092
B2C	-.413	-.302
B2G	.487	.512
Predictior variable		
AI adoption		.165
F	2.438	2.628
Adjusted R^2	.090*	.118*

Note. Coefficients are reported; *n = 74, ** p < .01; * p < .05; Significance* based on two-tailed tests; Dependent variable: Revenue growth.

For moderation analysis the same assumptions apply as with regression analysis, they did not need to be tested again. Moderation analysis is conducted via the PROCESS macro extension in SPSS. The model has an adjusted R square of .2024 indicating to a medium to high explanatory power of the model. Hypothesis 2 argues that the relationship between AI adoption and firm performance is positively influenced by the organizational tech level. However, the interaction effect of AI adoption and R&D investment on revenue growth is not significant with a p value of .4237 (Table 4). The moderator variable does not influence the relationship between AI adoption and revenue growth so hypothesis 2 is not supported. In Figure 2 a visual representation of the moderation effect in the model is presented. The blue dots represent low-tech organizations, and the red dots represent high-tech organizations.

Table 4

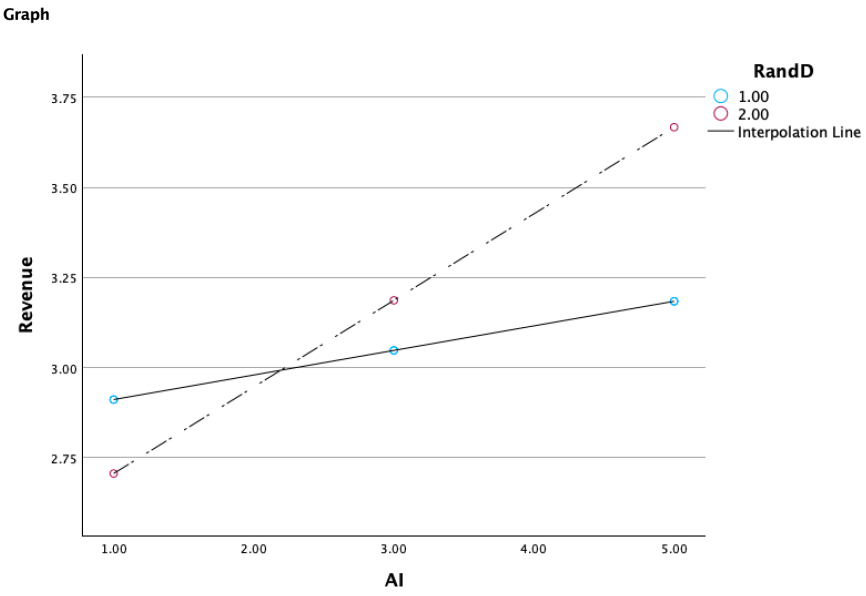
Moderation Results

Variable	Model
AI adoption	-.1039
R&D investment	-.3773
Int_1	.1721
Company size	.0001
Company age	-.2081*
Company valuation	.0470
B2C	-.2808
B2G	.4195
F	20.615
R^2	.2024

Note. Int_1 = AI adoption x R&D investment; * p < .05; Dependent variable: Revenue growth.

Figure 2

Plotted Moderation Effect



Note. RandD = R&D investment; The blue dots represents low-tech organizations, and the red dots represents high-tech organizations; X-axis: AI adoption; Y-axis: Revenue growth.

Discussion

Interpretations of Findings

This study examined AI as a growing innovation in business models of organizations. It sought to determine whether higher levels of AI adoption would lead to higher levels of Firm performance and whether this relationship is moderated by the tech-level of the organization. The following research question is answered: *"What is the effect of AI adoption in the business model on firm performance and does this relationship differ for high- and low-tech organizations?".* This study found no support for the proposed hypotheses suggesting that Dutch SME's are not able to leverage their AI adoption to enhance firm performance and this relationship is not different for high-tech and low-tech organizations. This study contradicts prior studies that have studied this relationship and calls for a more nuanced understanding of the performance implications of AI adoption. The outcomes of AI adoption seem to be not as straight forward as prior research suggests and other contextual and internal factors may have a strong influence on the success of AI adoption.

The main objective of this study was to examine whether higher levels of AI Adoption in the business model would yield higher levels of firm performance. Prior studies have researched this relationship and found that higher levels of AI adoption would lead to higher firm performance (Mikalef & Gupta, 2021; Lee et al., 2022; Baabdullah, 2024). These studies found that higher levels of AI adoption would help organizations with liberating routine tasks, reducing human error and biases, help discover new business opportunities, foster creativity and improve efficiency of decision making. Low levels of AI adoption would not lead to higher levels of firm performance as firms need to adjust to the technology and to fully leverage the technology complementary investments in cloud computing, infrastructure and more are needed (Lee et al., 2022; Haefner et al., 2021). However, this research does not find support for the hypothesized relationship and contradicts these other studies. The organizations in this sample do not show significantly higher levels of firm performance at higher levels of AI adoption.

The second objective of this study was to examine whether the relationship between AI adoption and firm performance is moderated by the tech-level of the organization. The distinction is made between high-tech organizations, who invest 5% or more of their revenue in R&D and low-tech organizations, who invest less than 5% of their revenue on R&D activities. High- and low-tech organizations differ considerably from each other which potentially influences the relationship between AI adoption and firm performance. Business models of high-tech organizations have higher technological complexity levels making organizations more suitable for AI adoption (Pavitt, 1984). Also, high-tech organizations invest heavily in R&D which according to Lee et al. (2022) is a necessary complementary investment to succeed with AI. However, the analysis of this study suggests no significant difference is found between high-tech and low tech-organizations for the relationship

between AI adoption and firm performance. Thereby the second hypothesis, the moderation effect, is not supported.

This research shows the organizations of interest, Dutch SME's, are not (yet) able to leverage their AI adoption to improve firm performance. Most of the organizations in the sample are still in the testing stage of adoption or at low levels (0%-5%). The AI technology is new for these organizations and as Haefner et al. (2022) and Lee et al. (2022) suggested organizations need to adjust to the new technology, reorganize practices around the new technology and acquire new knowledge. This is a process that takes time which may cause returns to be delayed. Other explanation could be that the technology as it is at this stage is not yet capable of delivering value to the average organization. As this research includes a wide variety of firms it may be therefore that there is no significant influence of AI adoption in the business model on firm performance.

Theoretical Contributions

By focusing on Dutch SME's, it provides valuable insight into the outcomes of AI adoption in a diverse business context. The findings of this study challenge the findings of previous studies, which suggest a positive relation between AI adoption in the business model and firm performance. This study highlights the importance of contextual factors like organizational readiness for the effectiveness of AI. From a theoretical perspective, this study contributes to the Resource-Based View (RBV) and literature on Business Model Innovation by examining the outcomes of AI adoption as a strategic resource that is added in the business model. According to the RBV firms generate competitive advantage by the acquisition of valuable, rare, difficult to substitute and difficult to imitate resources (Hart, 1995). The findings of this study highlight that the adoption of AI alone does not lead to significant firm performance and that as Lee et al. (2022) and Haefner et al. (2021) suggested complementary investments may be a necessity to leverage the AI technology.

Practical implications

In addition to the theoretical contributions, it also has a direct practical implication to investors and business owners. With the findings of this study investors and decision makers are better informed about the implications of the adoption of AI in the business model. This will help them make better and more informed decisions about investing in AI technology. This study highlights the need for a more nuanced understanding of AI adoption. It advises decision makers to research contextual factors influencing whether they can be successful with their AI technology before implementing them in the organizations. As the implementation of AI can be a time- and money consuming activity decision makers should carefully consider the readiness of the organizations before investing and implementing.

Limitations and Future Research

This study also has several limitations, and the findings should be considered in light of its limitations. The first limitation is that the study worked with a relatively small sample size which limits the generalizability of the findings. This is also related to the limited time available for this study. This study was conducted in a period of a little over 4 months. If there was more time available a more in-depth investigation of the relations could be conducted. The sample only included Dutch SME's, mainly due to feasibility reasons. This also limits the generalizability of the findings as no small (less than 20 employees), big (above 250 employees) and no foreign organizations were included in the study. To further investigate the implications of adopting AI technology in the business model of organizations future studies should firstly study this relation on a bigger scale. With a bigger scale study, it is possible to draw a more generalizable conclusion. To make any statements about why organizations are not able to leverage their AI technology a more in-depth study should be conducted to research different contextual and internal factors and.

Conclusion

This study examined the relationship between AI adoption in Dutch SME's and firm performance. This study found no evidence of a significant relationship between the adoption of AI in the business model and firm performance. Moderation analysis is conducted to examine if this relationship is influenced by whether an organization is high-tech or low-tech. No support was found for the moderation effect as well. This study contributes to the Resource-Based view and Business model innovation literature by examining the outcome of AI adoption in the business model as a strategic resource. Future research into this topic is advised to focus on the contextual and internal factors essential to the success of AI adoption.

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Appendix A: Survey Questions

Survey Question for Organizational Tech Level

1. How much of the revenue of your organization is annually spend on R&D?
    - Less than 5%
    - 5% or more

Survey Questions for AI Adoption:

2. How would you rate your organization's adoption of natural language processing (NLP) technology?
    - No adoption
    - Testing stage
    - 0%-5%
    - 5%-25%
    - 25%-50%
    - 50% or more
3. How would you rate your organization's adoption of computer vision technology?
    - No adoption
    - Testing stage
    - 0%-5%
    - 5%-25%
    - 25%-50%
    - 50% or more
4. How would you rate your organization's adoption of machine learning technology?
    - No adoption
    - Testing stage
    - 0%-5%
    - 5%-25%
    - 25%-50%
    - 50% or more

Survey Questions for Firm Performance:

4. What was your organization's revenue growth percentage in the last fiscal year?
    - Less than 0%
    - 0%-5%
    - 5%-10%
    - 10%-15%
    - 15%-20%
    - More than 20%
5. What is your organization’s projected revenue growth percentage for the coming fiscal year?
    - Less than 0%
    - 0%-5%
    - 5%-10%
    - 10%-15%
    - 15%-20%
    - More than 20%

Survey question for control variables:

6. How much employees work in your organization?
    - 20-50 employees
    - 50-100 employees
    - 100-150 employees
    - 150-200 employees
    - 200-250 employees
7. How old is your organization?
    - 0-10 years
    - 10-20 years
    - 20-30 years
    - 30-40 years
    - 40-50 years
    - 50 years or older
8. What is your organizations primary business model?
    - Business to Business
    - Business to Consumer
    - Business to Government
9. What is the current approximate value of your company?
    - 0-0.5 million €
    - 0.5-1 million €
    - 1-2 million €
    - 2-5 million €
    - 5-10 million €
    - 10 million € or above