The impact of artificial intelligence-powered primary value chain activities on the business model

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Titel:
The impact of artificial intelligence-powered primary value chain activities on the business model

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Abstract:
Os recentes saltos no desenvolvimento da inteligência artificial geraram investimentos consideráveis na tecnologia e criaram grandes expectativas quanto ao seu impacto potencialmente disruptivo nas empresas. No entanto, não existe consenso sobre a forma como a inteligência artificial pode afectar os modelos de negócio dos adoptantes e quais os factores que podem moderar essa relação. A literatura sobre o assunto é fragmentada e requer consolidação. Assim, esta tese realiza uma revisão sistemática da literatura académica existente sobre o impacto da inteligência artificial nos modelos de negócio, organizando as conclusões anteriores e apresentando um quadro holístico para a inteligência artificial e a mudança do modelo de negócio. A inteligência artificial está firmemente ligada e interligada com outras tecnologias digitais e deve ser considerada em conjunto. O impacto da inteligência artificial nos modelos de negócio é moderado pelo modo de adopção (desenvolvido interna ou externamente), pela presença ou entrada de uma nova empresa e pelo grau de digitalização da empresa e do ecossistema. A adopção da inteligência artificial não conduz necessariamente a uma inovação radical do modelo empresarial, mas, na maioria dos casos, resulta apenas numa mudança incremental do modelo empresarial. Os modelos empresariais baseados na inteligência artificial geram e proporcionam regularmente um valor acrescido, mas a captação de valor não depende directamente da inteligência artificial, mas de outros factores estratégicos. Esta tese propõe um quadro holístico para o impacto da inteligência artificial na mudança do modelo empresarial, a fim de orientar a investigação futura e os profissionais na gestão da inteligência artificial.

Keywords:
Inteligência artificial, Aprendizagem automática, Modelo empresarial, Inovação do modelo empresarial

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Abstract:

Recent leaps in the development of artificial intelligence have generated considerable investments in the technology and created high expectations for its potentially disruptive business impact. However, there is a lack of consensus on how artificial intelligence may affect adopters' business models and which factors may moderate that relationship. The literature on the subject is fragmented and requires consolidation. Thus, this thesis conducts a systematic review of the existing academic literature on the impact of artificial intelligence on business models, organising prior findings and presenting a holistic framework for artificial intelligence and business model change. Artificial intelligence is firmly connected and interlinked with other digital technologies and should be considered in combination. The impact of artificial intelligence on business models is moderated via the mode of adoption (internally or externally developed), incumbency or new entrance of the company and digitalisation degree of the firm and ecosystem. Artificial intelligence adoption does not necessarily lead to radical business model innovation but, in most instances, only results in incremental business model change. Artificial intelligence-enabled business models regularly generate and deliver increased value, but the value capture is not directly dependent on artificial intelligence but other strategic factors. This thesis proposes a holistic framework for artificial intelligence's impact on business model change to guide future research and practitioners in managing artificial intelligence.

Keywords:

Artificial intelligence, Machine learning, Business model, Business model innovation

Executive Summary

Artificial intelligence's impact on business models cannot be considered in isolation, as it is connected to the impact of digitalisation overall. Artificial intelligence requires suitable data collection, storage and processing capabilities, and the strategic relevance depends on the complexity of the underlying data assets.

Overall artificial intelligence adoption predominantly leads to incremental business model change, but the adoption by new entrants and first movers increases the likelihood of radical change. The relationship between radical business model change and artificial intelligence is further mediated via management support and understanding of the technology and moderated via the origin of the artificial intelligence, i.e. internal or external development.

However, new entrants powered by artificial intelligence do not necessarily disrupt the industry by radically innovating but often only complement the incumbents' business models. The dynamic of radical and incremental business model change may depend on the complexity of the data assets for artificial intelligence training.

For managers to anticipate the effect of artificial intelligence on their business models, it is necessary to (1) explicate the existing business model, its components and logic, (2) understand the essential opportunities artificial intelligence offers, (3) identify the applications of artificial intelligence to create, deliver with increased efficiency and capture more value and (4) assess the complexity of the data assets required to develop the artificial intelligence. Artificial intelligence alone is unlikely to allow for (sustained) superior performance. However, it can be a source of great value to a company when grounded in complex data assets, complementary offerings, lock-in effects, and high business model fit.

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1 Introduction

The advent of ChatGPT as an artificial intelligence tool has enhanced the prevalence of artificial intelligence in all areas of modern life. It especially indicates new challenges for the business world. Technological progress has been shaping the business agenda for the last two decades and created the need for large-scale changes in strategy, processes and operational management while also pushing the business model as an intermediate layer between the business processes (value activities) and the business strategy to the forefront of researcher's agendas (Al-Debei & Avison, 2010).

The concept of business models (Snihur & Eisenhardt, 2022) has been consolidated and systematically reviewed by scholarly publications, as has the business model innovation research generally (Filser et al., 2021), and particularly for digitalisation-induced business model innovation (Sorescu, 2017). Artificial intelligence and its business model implications have, however, until now only received limited attention and while there are some first efforts to combine the existing findings, the existing literature reviews address only subcomponents of the business model and artificial intelligence relationship (Mariani et al., 2023). There have also been some literature reviews about specific business model changes and artificial intelligence (Di Vaio et al., 2020), for instance, in the sustainability field, but none investigating the impact of artificial intelligence on the business model on a fundamental level and from a holistic perspective. Thus, this is a yet non-reviewed area, which due to its interdisciplinary nature, shows a high fragmentation and requires consolidation.

Hence, this systematic literature review investigates the impact of artificial intelligence adoption and implementation on the business model. The definition of the business model is based on Teece (2010). The adoption of artificial intelligence is only considered relevant if it is deployed as a crucial and key part of the firm's operations, thus requires to be implemented in the firm's primary value chain activities, based on the value chain concept of Porter (1985). For this literature review, contributions investigating artificial intelligence in non-essential and support activities were excluded, as well as purely hypothetical applications of artificial intelligence that were not implemented or not at operational capacity.

The research question is thus defined as:

Research Question: How does the predictive logic of artificial intelligence-powered primary value chain activities and processes impact a firm's business model?

The goal of this review paper is to (1) recap the existing literature on the topic, (2) establish a theoretical conceptual framework and (3) identify future research areas requiring further investigations.

In the first part, the concepts of business models, artificial intelligence and artificial intelligence applications in business will be recapitulated based on a narrative review of the most relevant literature. Based on those theoretical foundations, a conceptual understanding of the potentially relevant factors of artificial intelligence's impact on business models will be established, and four hypotheses for the review will be proposed. The second part will be a systematic literature review structured according to the proposed hypotheses and the nature of artificial intelligence's impact on the business model. Firstly, the direction of the impact will be investigated, followed by considerations of the nature of artificial intelligence's impact on business models (incremental or radical change), the impact on the different business model dimensions and lastly, artificial intelligence and business model sustainability. This structure will allow for identifying and understanding the business model change that artificial intelligence facilitates.

2 Establishment of concepts

The business model and artificial intelligence adoption are two relatively fuzzy concepts with a short research history and thus require to be defined in detail.

2.1 Artificial intelligence

Artificial intelligence has been at the forefront of public interest ever since the launch of ChatGPT end of November 2022, with countless news articles in specialised (Criddle & Bradshaw, 2022) and by popular newspapers (Fowler & Merrill, 2023) discussing its impact on the economy, labour, investing and daily life. However, while this topic has enjoyed incredible attention from the business side, especially in practitioner circles of management, there is a surprising lack of basic understanding of what artificial intelligence is, what it can do and where its boundaries lie. This leads to an overuse of the term to the degree of a buzzword, which inhibits the proper identification of opportunities and risks and appropriate responses.

A broad definition of artificial intelligence from Professor McCarthy states:

> It is the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but artificial intelligence does not have to confine itself to methods that are biologically observable. (McCarthy, 2007, p. 1)

While based on this definition, a myriad of different techniques and approaches can be subsumed in artificial intelligence, the current wave of interest is mainly based on the application of deep learning, an extended technique of neural networks, and part of the artificial intelligence subcategory of machine learning. Overall, the business-relevant artificial intelligence, i.e. artificial intelligence applied by businesses in different functions and areas, is nearly exclusively from the machine learning field (Sarker, 2022). The technique behind ChatGPT, for instance, is a very large deep-learning neural network trained on huge data amounts from the internet using a supercomputer’s processing power (Ruby, 2023).

Within the field of machine learning, there are different subcategories, listed in decreasing current importance for businesses. First, supervised learning is the most developed and used with techniques such as deep learning. The second is transfer learning, which allows facilitating

a model trained on different data sets in another environment, followed by unsupervised learning, which is currently a popular step in the data preparations (e.g. Principle-Component-Analysis) or for clustering applications (K-Means) and lastly, reinforcement learning, which is mostly decision making by optimisation (Ng, 2016).

As nearly all of the currently used artificial intelligence technologies are machine learning applications, as exemplified by statistics of artificial intelligence technologies applied in the Nordics (Silo AI, 2022), several fundamental characteristics hold for all of those models. First every machine learning application is trained on a training data set, a so-called input. Different techniques will interact differently with this data set, but all of them will need to be provided with an input. This input is then used to perform a series of operations. In the case of a tree model, which will be used as an example through this explanation as it is the most intuitive, the dimensions of the data will be searched for a split resulting in the highest reduction in entropy. Entropy is a measure of chaos in the data. In simple terms, if the data would have two categories and only one category is present in the data sample, the entropy would be zero, but if there is a fifty-fifty split it will result in the highest entropy possible. The tree algorithm investigates every dimension (feature) of the supplied data and will create a split in the data, meaning it will create subgroups over the dimension where the entropy reduction is greatest. The result is two branches of the tree with one split criterium. It will repeat this procedure until either there is nothing to split, i.e. one observation by data subset, or when complexity controls are fulfilled. Complexity controls are, for instance, maximum tree depth (Maximum number of subsequent splits to be performed), minimum pre-split size (Minimum number of observations in subset to split data) or a general complexity penalty. The outcome of a tree algorithm is, in a classic application, a classification, i.e. the observation provided as input is either part of a category or not. It can, however, be used in the prediction of amounts with slight modifications (James et al., 2013).

Generally, it can be stated that the outcome of any supervised learning model is either a value or a classification. While this seems not to do justice to a complex model such as ChatGPT, it is very similar to what happens in such a large complex language model. First it learned what type of answer it should predict to a specific question, starting based on a training data set that it was provided with, e.g. an online forum. Then based on the letters and words of the question, it will come up with several words in a specific order that, according to its training data set, are most likely correct based on the model. While the reality is more complex, and this is a

simplification, this is what happens in basic terms. This dependency on the training data set is also why the reliability and correctness of answers of generative artificial intelligence are always questionable, as they are solely depending on the training data set it was exposed to, and there is always a certain degree of error, i.e. bias, present. The second issue with current artificial intelligences is their nature as black boxes, as they are not explaining the reasoning behind the outcomes provided, and as recent research has shown, they do not develop an genuine understanding of the matter but just develop rules and algorithms based on the training data, which have weak points that can be exploited using specific strategies (Wang et al., 2022).

In the end, any machine learning mechanism can only use the training data it was provided with and cannot differentiate between highly reliable and non-reliable information, but depends on the labelling of the data and, hence, is mainly based on measures as such as frequent co-occurrence. Moreover, as a result, current machine learning techniques are entirely inept at predicting something in changing external circumstances as their prediction relies on the assumption that the past has predictive implications for the future, which in the case of an exogenous shock does not apply.

In basic terms, machine learning is a technology as was the introduction of the steam engine, the computer and search engines. As such, it extends existing boundaries of strategic thinking and operating possibilities. Simply put, it enables new processes and activities that would not have been possible before. For example, the creation of the steam engine made it possible to convert fossil energy into mechanical energy, which in turn allowed to build machines able to use this energy to move people and wares faster, produce larger objects, or increase the speed of production. By itself, the steam engine did not have any relation or specific impact on any industry's or company's business model but constituted a shift in opportunities and risks for all of them.

Artificial intelligence shares this characteristic, but instead of coal it uses data. Artificial intelligence as technology is not confined to any specific field or application but can be used in many different ones. This is also one of the main reasons why the field of artificial intelligence appears so fragmented to the outside, as there is a mixture between the basic technologies and optimised versions of it for specific applications. For example, while ChatGPT is a machine learning application using mainly the technique of deep learning, it is functionally a large language model and belongs as an ensemble model to the machine learning category of

supervised learning and some parts to the reinforced learning category. An ensemble model only means that there are several machine learning techniques, in the ChatGPT case, deep learning and reinforced learning stacked on top of each other (Ruby, 2023). The value of artificial intelligence and machine learning derives from their ability to manage unstructured and tremendous amounts of data. In 2020 the data generated is 32x the data from 2010, with the trend continuing in an exponential trajectory (DC & Statista, 2021) and those amounts of data are too large to make any sense of them with a basic human's analytical brain power or traditional business analytics methods. Artificial intelligence, on the other hand, can handle thousands of dimensions of data and find patterns in them that humans would not be able to detect.

The core logic of any artificial intelligence is to detect patterns in data. An artificial intelligence is given a specific input and will provide an output. Combining artificial intelligences into ensembles can lead to very impressive results, but the basic building blocks remain the same. Depending on the technique and combination thereof, the output artificial intelligence delivers may be a clustering, classification, prediction of an amount or a suggested action.

Therefore, the specific type of artificial intelligence is not expected to have a specific business model impact associated with it and thus, it will not be necessary to differentiate between the different machine learning models applied, as all machine learning technologies have more or less the same core predictive logic underlying and even models such as expert systems, are based on data inputs by experts that create a form of decision rules and generate an output to a specific question. Thus, as is also suggested by Magistretti et al. (2019) and Brynjolfsson et al. (2017) artificial intelligence should be developed and understood as a general-purpose technology with applications in many different areas. This is also reflected by the analogy in the functions of steam engines to artificial intelligence as described above. Steam engines were the prime example of general-purpose technologies from Bresnahan and Trajtenberg (1995).

2.2 Artificial intelligence-powered value chain activities

One of the main issues in this thesis is the definition of the required function artificial intelligence needs to take to be considered relevant in this review. In the business environment, there are many more or less visible and consciously used artificial intelligences. Hence, a prior

definition of which type of artificial intelligence will be considered as relevant is required. Artificial intelligence is used in many third-party programs applied in nearly any company; thus, the sole presence of artificial intelligence in any form does not provide a sensible independent variable to base research on. In the most basic terms, artificial intelligence needs to be used in some essential and conscious form to impact any business model component. For example, considering artificial intelligence usage when employees use the search engine *Google Search* (the Google algorithm does count as an artificial intelligence) would classify any company as having artificial intelligence usage and would not present any valuable insights. For research practicality, the value chain concept of Porter (1985) will be used, and the review will focus on artificial intelligence applications in the primary value chain activities, thus, inbound logistics, operations, outbound logistics, marketing and aftersales. Support functions' use of artificial intelligence will not be considered. This is done from a business model perspective, as it is most relevant to look at the value-creating activities for the customer, and while the efficiency of running the finance and human resources department impacts the overall cost structure and the price, and thus the value the customer can receive, the product value does not derive from those functions but from the primary value chain activities.

Different applications of artificial intelligence even within the primary value chain activities may have different levels of prominence and relevance to the business value created as a whole and the business and management culture, which does imply different impacts of artificial intelligence on the actual business models. However, there is little distinction made in the literature between applications of artificial intelligence in different value chain activities, as well as actual importance to the company's culture and management. This is a shortcoming of the methods employed by several researchers on the topic, as artificial intelligence, especially in the start-up sector, regularly is used as a buzzword (Herrmann, 2022), and does not necessarily constitutes any importance to the business, which risks falsifying results, as supposed artificial intelligence companies in truth do not apply artificial intelligence to any significant effect, mixing potential impacts of artificial intelligence applications with non artificial intelligence applications and in result skewing the effects downwards. Overall, the definition of what constitutes a relevant artificial intelligence application for business model impact constitutes the first gap in the literature and requires further empirically based consideration.

For instance, artificial intelligence used in the supply chain (inbound logistics) for creating operational efficiency in a manufacturing facility, potentially using a third-party developed artificial intelligence solution, has a very different implication for the business model than for example, artificial intelligence used for customer segmentation or even personalised pricing in the sales and marketing activities. Hence, the first proposition is that the exact location and extent of the artificial intelligence use within the value chain is potentially the first relevant moderating factor for its impact on the business model.

This thesis's second proposition states that the origin of the artificial intelligence is potentially highly relevant to consider as a moderating factor as well. For instance, using a third-party developed ready-to-deploy artificial intelligence will have less impact on the business model, possibly resulting in solely incremental improvement of some parts of the business model. In contrast, an internally developed artificial intelligence indicates not only strategic relevance but also capabilities and culture changes, which may relate to larger and more radical business model changes.

The third proposition states that the goal of the artificial intelligence will potentially act as a moderating factor as well. Besides the location in the value chain, it could also make a difference if an artificial intelligence would be used to create revenue for the company, as in the example of *Uber*, where artificial intelligence supply and demand management allow for efficient operations and are the core of the value creation within the value chain or if artificial intelligence is simply used to increase efficiency and for cost reductions, which is paramount for any organisation to achieve long term performance but probably does not show the same amount of importance to the long term business model impact. This is potentially related to the amount of management attention the artificial intelligence receives. If it is a crucial variable impacting both the top line and the cost side, top management will expend more energy on understanding and optimising the artificial intelligence than in case of a purely cost focussed niche application where especially senior management will only check results but is not expected to try to understand or tweak the mechanism behind, as it is of much less relevance. Therefore, the (top) management's understanding of artificial intelligence could be a highly relevant mediating factor for the business model impact as the organisational culture in the top management is very relevant for the general business model choice (Chesbrough, 2010), and understanding of the artificial intelligence and its functions may shape the decisions-making

and opportunity and risk perception as well as interpretation in accordance with bounded rationality (Simon, 1957).

Thus, to sum up, there are three basic considerations that will be considered as moderating variables in the following literature review (1) the location and extent of artificial intelligence use in the value chain, with a purely primary activities focussed approach in this thesis, (2) the origin of the artificial intelligence, i.e. fully outsourced our in-house developed and (3) the nature of the artificial intelligence use from revenue growth-oriented to pure cost efficiency improvement.

2.3 Business model

The concept of business model has been under critique as being undefined and susceptible to faulty thinking (Porter et al., 2001), however, countless academic publications and usage of practitioners in the last 20 years, have shown a high relevance of the concept and currently there is a trend of convergence in terms of the concept evident (Wirtz et al., 2016). The original work and concept stem mainly from the information system field, and thus in the beginning were used to describe the digital business models in the early 2000s (Al-Debei & Avison, 2010). The shift in the way business was conducted in the early 2000s due to the advent of the internet creating new opportunities for companies to conduct business but also creating a gap between the high-level strategic perspective of the firm and the underlying process level. As such the business model acts as a conceptual tool for alignment between the increasingly disconnected strategic objectives and the processes of the firm in the form of technological artefacts and is lodged in between the operational business process model and the highly aggregated strategy. Another function of the business models is as a tool for knowledge flow enhancement in the company by effectively communicating the core of the business logic to the stakeholders facilitating knowledge sharing and potentially leading to better fit and alignment of the business model with the industry opportunities, the customer's needs and the internal resources and capabilities (Al-Debei & Avison, 2010). Further digital businesses, e.g. platform businesses, require the coordination of a complex set of partners in a network (Haaker et al., 2006); the classical strategic theories, while able to explain the superior performance of firms in certain areas are not able to capture and communicate the complex reality of those dynamic and

interdependent value creation and capture mechanisms, which however are essential for understanding and navigating the landscape of digital businesses.

The definition applied in this research for the business model is based on Teece (2010):

> A business model (…) describes the design or architecture of the value creation, delivery, and capture mechanisms [a firm] employs. The essence of a business model is in defining the manner by which the enterprise delivers value to customers, entices customers to pay for value, and converts those payments to profit. (Teece, 2010, p. 172)

This definition will be used throughout this thesis. The components of the business model consist of the value proposition, revenue model and cost model (Osterwalder & Pigneur, 2013). The value proposition is made up of geography, product and service and customer needs, the revenue model by customer interaction, channels and price logic and the cost model by core assets and capabilities, partner network and core activities.

The business model is not the same as a strategy (Teece, 2010), however inextricably linked to the big questions strategy tries to answer, as it is the blueprint, the more detailed and implementable version of the more general vision of strategy. As such a business model can be viewed basically as a translation of strategical considerations in a more practical and executable format, required to develop business processes. Only the choice of a proper business model allows one to achieve the superior performance strategy seeks and, as established in the business model literature (van Angeren et al., 2022), the main driver of the success of business models is the fit of the business model to the product, market, customer needs and resources and capabilities.

Generally, it must be stated that as for a for-profit business, the final goal in any decision-making is the value creation for the company, the consideration of the impact of artificial intelligence implementation on the business model, must be interlinked with strategic thinking. Considering this link to the strategy literature there two frameworks are most relevant to artificial intelligence applications. Firstly the resource-based theory (Barney, 1991) for artificial intelligence applications related to incremental improvement of capabilities, and secondly the dynamic capabilities, for artificial intelligence applications that come as disruptions to their industries and as such represent an exogenous shock (Teece, 2007). Lastly, the upper echelons theory (Hambrick, 2007) may also offer some explanatory power for the top management's

understanding and support of artificial intelligence. While artificial intelligence is viewed by some as necessarily representing an exogenous shock, this thesis will argue that artificial intelligence may constitute an exogenous shock in some circumstances, but in others behaves in a relatively linear and incremental manner. This distinction will be investigated further at a later stage.

Business model impact in its most basic conceptional sense is the change or non-change of certain components of the business model and the degree of the change. Business model innovation is a significant business model change in the value creation, delivery or capture (Mariani & Nambisan, 2021). A business model change can also be a small change within the business model, i.e. for example improvement of the value delivery due to efficiency improvement in the cost structure or adding one new offer, actual business model innovation requires larger modification of the business model, at least changing one of the three value dimensions profoundly. In consequence, the difference between business model change is also dependent on the complexity and size of the business. If a company adds one new product with a servitisation revenue model, there is a difference in the degree of business model change between a company with 100 products and one product on the market.

A radical business model shift, requires a fundamental change to the current business model, upsetting the existing order. Incremental business model change on the other hand is only an improvement of a business model component, that does not fundamentally change how business is conducted. Radical change and business model innovation are not equivalent. Radical change describes the change to an existing business model, while business model innovation may also stem from new business model design of new market entrants for instance. The question is in how far, radical business model innovation can happen via incremental steps, for example the addition of one product as described, and subsequent revenue growth and discontinuation of the other product would arguably constitute a radical business model change, as the old business model would have been overhauled in nearly every component and resulted in a substantial change to the firm’s value proposition (Sorescu, 2017).

2.4 Artificial intelligence and business models

Artificial intelligences, rather more precisely the artificial intelligences developed from 2013 onwards using a superior algorithm (e.g. neural networks in supervised learning) and increased availability of data and processing power, can present themselves to the market as radical technology change, as it has the potential to impact business model architecture on all conceptional levels (value creation, value delivery and value capture) as well as in all of the components (Processes, capabilities, ecosystem etc.) (Sena & Nocker, 2021). The impact of artificial intelligence on the business model can be considered from two perspectives: Firstly, from the strategic side focussing on the impact of artificial intelligence on strategic decision-making and how this affects the business model top down, which is very relevant for practitioners and uses the dynamic capabilities framework as a basis (Teece, 2007) and secondly the overall impact of artificial intelligence on business models, which approaches the bottom-up approach. In this review we will consider both perspectives but with a special focus on the latter.

2.4.1 Strategic perspective on artificial intelligence's business model impact

The most relevant impact simply put is the extension of opportunities and risks into previously economically not feasible areas. While for example, a full value capture of all created value was historically an interesting thought experiment, it was a non-practical concept in most situations and industries. Here for example the advancement in predictive capabilities potentially allows the extraction of additional surplus customer value, due to increased predictive capabilities from advanced artificial intelligence algorithms allowing for improved prediction of the respective willingness to pay per customer and in complement with the technological possibility of IP tracking, cookies, and user account data, to charge a user close to her actual willingness to pay, which increases the efficiency of the market (Grewal et al., 2021).

Nevertheless, considering this shift in overall value capture away from the consumer does not necessarily implicate an increase in value creation for the customer. This is where the relevance of business model design and its boundaries gain special relevance. For a company to successfully leverage artificial intelligence it is not enough to simply shift the frontier of value

capture from the consumer to the supplier side, but it is much more relevant to control the strategic bottlenecks of the changed value creation chain, as has been found in strategy and digitisation literature (Teece, 2010). The question here is which capabilities and resources prove themselves to be core competencies (Barney, 1991; Grant, 1991), in the newly developing value chain based on artificial intelligence capabilities. The identification of those resources and capabilities may tend to prove the most critical aspect of artificial intelligence adoption and its impact on the business model, as the business models need to be structured around exactly that value controlling point, and in the reality of complex ecosystems (Chen et al., 2021), this will prove to be a highly challenging management task. Interestingly, however, the artificial intelligence component impact on this will be potentially relatively low, as the technology itself in most cases does not constitute this value bottleneck, but most often the correct adoption and fit of a business model (Teece, 2018). Thus, the algorithm and technology adoption is not the main issue, but rather the surrounding factors and elements may constitute the limiting and thus decisive elements. Among them most prominently is the availability and proper storage of the required data, without which artificial intelligence cannot be trained for the required tasks, the human capital, which can, firstly, identify relevant artificial intelligence value creation opportunities and secondly build the custom-made algorithm required, and lastly the immense computing power required for the training (Provost & Fawcett, 2021).

2.4.2 Artificial intelligence and business model impact a general framework

The business model may be impacted in different ways depending on the origin, location, and goal of the artificial intelligence.

From a research field approach to business model literature, there are three business model research strands especially relevant. Firstly, the business model innovation literature is mainly concerned with the rapid and extensive change of business models, through which many of the elements of an existing business model are transformed. Secondly via business model change research, focused on slower more narrow and incremental changes, i.e., only in one or a few business model components. Thirdly the business model design literature focused on the mechanisms of why a business model is set up and created in its respective form. For the artificial intelligence impact, all of those research strands are relevant as they help to understand how business models may change or be designed differently due to the influence of artificial intelligence's predictive logic (Filser et al., 2021). This indicates that the research on the impact

of artificial intelligence on business models can be split into literature focussing on incumbents of an existing market adopting artificial intelligence and artificial intelligence adoption by new market entrants. The former is related to the literature stream of business model innovation and change, and the latter to business model design.

However, besides the relevant research strand terminology, there is a more conceptual understanding of the impact a new technology may have on the business model. In terms of artificial intelligence characteristics, there are conceptionally several factors which could potentially influence the impact on the business model at the company and the industry level.

At the company level three main dimensions may influence how the business model may change as explained above (1) the location of artificial intelligence use in the value chain, with a purely on primary activities focussed approach in this thesis, (2) the origin of the artificial intelligence, i.e. fully outsourced our in-house developed and (3) the nature of the artificial intelligence use from revenue growth-oriented to pure cost efficiency improvement.

On the industry level, the proposition is that the origin of the artificial intelligence applications industry-wide is of high relevance. The main question is who the first mover in terms of growth-oriented artificial intelligence has been in the industry. There are two possibilities: (1) artificial intelligence application is brought by new entrants (most often start-ups), which can potentially be disruptive for the industry and (2) artificial intelligence is introduced by the incumbents, which may rather tend to incremental, step by step change of the business models.

Business model change can happen in two dimensions, Firstly, where the change is occurring, in which components and in how many and secondly the nature and degree of the change, which can be from incremental to radical. This conceptual understanding will be further used to build a framework for the literature review.

Summing up the business model could be impacted in three different ways. Firstly, artificial intelligence use by the company might not have any impact on the business model choice, i.e. there is no change observable. Secondly, artificial intelligence may have an incremental impact on the business model, by only changing components or subcomponents, or thirdly artificial intelligence may have a radical impact on the business model, by affecting several different components at once and changing the way value is created, delivered, and captured by the

company. For radical change to occur at least one of the main dimensions of the business model, i.e. value creation, value delivery or value capture needs to be fundamentally changed.

This understanding leads to the first hypothesis of this thesis:

Hypothesis 1: There is a direct proportionality between the extent of implementation of artificial intelligence in the primary value chain activities and radical change in the business model and vice versa.

The premise of this hypothesis is that artificial intelligence applied commonly along the value chain, will lead to radical innovation in the business model while only small applications in parts of the value chain will only lead to small and incremental business model adjustments.

Further, the origin of the artificial intelligence should show a varying impact on the business model. If an artificial intelligence is in-house developed this should facilitate radical change in the business model while externally sourced artificial intelligence should lead to only incremental or no changes in the business model.

Hypothesis 2: The origin of the artificial intelligence is linked to the type of change occurring, higher in-house participation/ development leads to an increase in the amount of change in the business model.

Moreover, the goal of implementation of artificial intelligence is also linked to the type of change in the business model.

Hypothesis 3: Artificial intelligence applications oriented towards improving the cost structure and increasing efficiency result in incremental business model change.

There is most likely a link between who introduced artificial intelligence into the industry and the impact on business model change.

Hypothesis 4: Artificial intelligence introduction by external entrants will more likely lead to radical changes and disruption of the industry, upending the incumbent’s business models.

3 Methodology

To investigate the research question a systematic literature review will be conducted, as this type of review process tends to be more transparent and replicable and thus is defined by higher scientific rigour (Tranfield et al., 2003). The search will be keyword based, as this process of the literature search is well suited for an interdisciplinary topic (Seuring & Gold, 2012). This research is interdisciplinary as it encompasses issues from entrepreneurship, business model, strategy to IT and technology innovation. The database used was EBESCO Business Source Complete, as it not only contains a comprehensive selection of business and management journals but also includes journals in the fields of information systems and engineering, which are of particular interest to this review, due to the technological aspect of artificial intelligence (Charvet et al., 2008).

The selection of articles was based on (1) their relevance to the research question and (2) the quality of the research method. There were three search cycles employed. The period for the search was from 1988 to January 2023, with only articles from peer-reviewed academic journals in the English language being considered for further investigation. In the first search round a highly constricted search with the keywords *business model or business model innovation or business model choice AND artificial intelligence or artificial intelligence or a.i. or machine learning or deep learning or neural networks AND predictive analytics or predictive logic or prediction or forecast* on the EBSCO Business Source Complete was performed yielding a total of 111 articles. In the second round the keywords were slightly less restricted, *business model or business model innovation or business model choice AND artificial intelligence or artificial intelligence or a.i. or machine learning or deep learning or neural networks*, resulting in 378 articles using the same criteria as above and after excluding the publication artificial intelligence *Practitioner*, which does not have an artificial intelligence but a focus on appreciative inquiry (Godwin et al.).

The resulting article's abstracts were inspected for containing the two main components, artificial intelligence and business model, of the research question. Only articles with employed and implemented artificial intelligence technologies were included in the review. Hence, articles only considering hypothetical artificial intelligence models for an industry were excluded. After this initial round of validation, 55 articles were remaining, which were in-depth

checked for their methodology and scientific approach and relevance to the research question, leaving 18 articles for review. Respective exclusion reasons per article for the methodological assessment can be found in the Appendix.

Considering the high fragmentation of the literature on the subject, it was necessary to ensure coverage of all potential contributions. To increase the coverage of the selection, in the third round, the snowball method was applied, to supplement the previous selection. This was done by reviewing the reference list of high-quality publications on the topic with a VHB rating of minimum A (VHB, 2023) and identifying additional relevant literature. The snowballing method is a good fit for research with keywords that are general terms (Jalali & Wohlin, 2012), and due to the inflationary use of the terms artificial intelligence and business model within academic literature well suited to this research. The result of the snowballing methods were 32 additional articles, with after in-depth investigation resulted in 11 additional review articles. Articles were included and excluded based on the same criteria as above. The resulting list was combined with the selection from rounds one and two. An exhaustive list of results and inclusion and exclusion reasoning can be found in the Appendix. The resulting articles were analysed using conceptional synthesis (Rashman et al., 2009), deviating from the orthodox approach of systematic literature analysis, as the resulting selection of contributions is mainly of qualitative nature, and does not allow for quantitative synthesis.

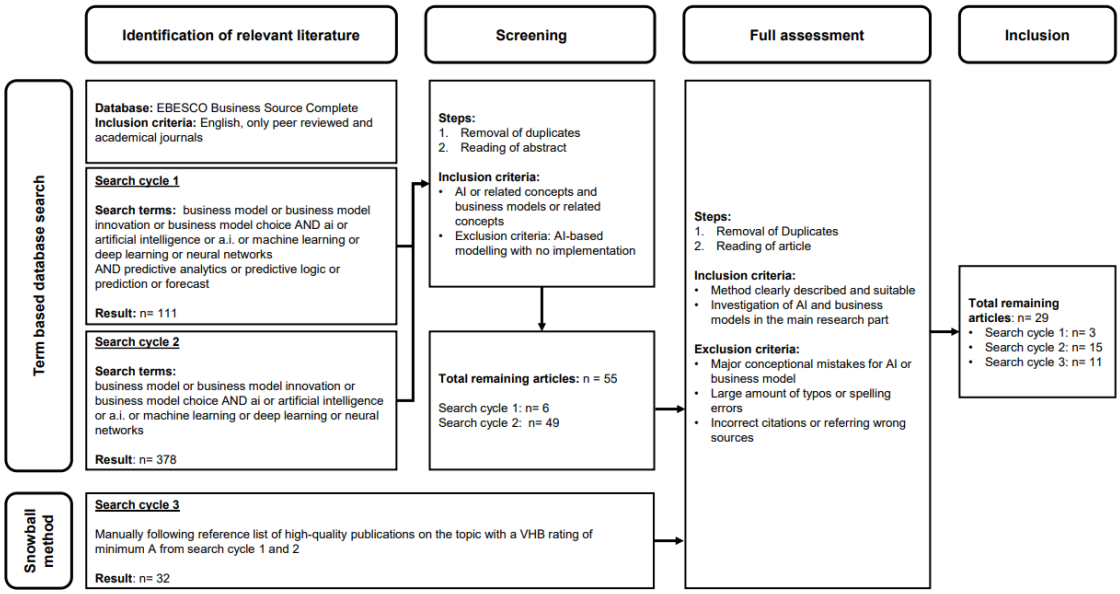

Figure 1: Summary of methodology and search cycles

Source: Based on Moher et al. (2009)

4 Literature review

When investigating the literature regarding the business model impact of artificial intelligence implementation, it becomes apparent that the direction of impact, i.e. artificial intelligence affecting the business model cannot be assumed as given. In many cases it is rather the business objective of transforming one's business model to, for example, servitisation, driving the application of artificial intelligence in the operating activities (Brooks et al., 2020; Iansiti & Lakhani, 2020; Sjödin et al., 2021).

4.1 Direction of impact artificial intelligence and business model

For instance, in a case study on several manufacturing companies, this dynamic has been found by Sjödin et al. (2021), suggesting that manufacturing companies try to develop artificial intelligence capabilities to be able to achieve a business model transformation from providing certain goods to servitisation. This suggests radical business model change, but the direction of the change is exactly the opposite direction. Business model change aspirations lead to the implementation of artificial intelligence in this case not the other way around. This might be due to the sector of this paper, as the manufacturing sector traditionally is a rather cost focussed sector and not among the leader in technology adoption but does suggest a vice-versa dynamic than assumed.

In line with those results Iansiti and Lakhani (2020), argue that companies should develop the artificial intelligence capabilities needed to be able to compete in the new data-driven business environment and change their business model. They develop the understanding further by showing, via company examples such as Alibaba's Ant Financial which started at its core as an artificial intelligence-powered company and new entrants to their market, that artificial intelligence applications may lead to different business model designs. Fintechs shifted the traditional banking business to online, thus bringing radical change to the business model and impacting all the components of the value chain of the incumbents. Artificial intelligence-enabled, radical change in the way the business operates and sells its services to customers, and has led to a radical change in business model, relying heavily on networks and ecosystem partners in comparison to the more traditional banking sector. This indicates that first, an artificial intelligence-powered company needs to provide proof of commercial concept for a

specific artificial intelligence application, radically changing its business model, which in turn leads to greater artificial intelligence adoption and consequent business model changes for incumbent companies of the industry. Those findings suggest that the direction of impact changes depending on the type of company (incumbent, new entrant) and the innovation position (first mover or follower). Artificial intelligence impacts the business model, when the incumbent is the first mover, while when the incumbent is a follower business model innovation aspiration may lead to artificial intelligence adoption, begging the question if and how artificial intelligence drives the business model design of the first movers when they are new entrants to the respective market.

This dynamic has been found in several different sectors, including the legal profession, where in an interview-based case study, Brooks et al. (2020), find that artificial intelligence adoption is overall low for the incumbents of the legal profession. Current applications are mainly related to the automation of specific tasks, and only affect some parts of the value chain, with cost reduction being the main goal for the applications. Some of the studied firms employed technology experts themselves but predominantly the artificial intelligence solutions were externally sourced. The resulting business model innovation is incremental, improving mainly the cost structure. However, new entrants namely legal tech, push the incumbents to explore new applications of artificial intelligence. This push is currently counterbalanced by a low willingness to change, cultural and organisational lock-in effects and risk adversity (Concerns regarding data and GDPR) of the industry. Missing understanding of the artificial intelligence by the partners is named as another factor impeding investment and application of artificial intelligence. Those findings reinforce the results from other industries, by first illustrating a link from limited application along the value chain, efficiency-oriented use and externally sourced artificial intelligence to incremental business model change and highlighting the importance of new entrants changing the business model paradigm of the industry. It adds to those findings, by emphasising the moderating role of the cultural and organisational lock-in effects, risk adversity and missing understanding of the technology, which all reduce artificial intelligence adoption and radical business model change. This may indicate that the legal industry in the United Kingdom currently even though new entrants with artificial intelligence technology have arrived is not disrupted.

The mechanism for disruptive business model innovation indicated above was attributed by Sena and Nocker (2021) to value migration. In value migration, radical business model

innovation by a competitor using artificial intelligence (incumbent or new entrant) triggers business model innovation for the other market participants. This would link to the findings above focussing on artificial intelligence applications in start-ups impacting the business models of the industry. They find four business model archetypes that may result from artificial intelligence: Processes and automation, improving customer interface, joining ecosystems and developing smart products.

In summary, the direction of impact between artificial intelligence adoption and business model is depending on the company being an incumbent and a first mover or follower. It also becomes apparent that artificial intelligence's impact on business models not necessarily is radical but in many cases is rather incremental. New entrants based on artificial intelligence may have a disruptive effect on the industry, leading to radical business model change (Jin & Shin, 2020), but that is not necessarily the case (Aloini et al., 2022; Anton et al., 2021; Garbuio & Lin, 2019).

Business model innovation may be radical, as exemplified by Jin and Shin (2020) when investigating the impact of potentially disruptive artificial intelligence-enabled business models in the fashion industry. Researching a subscription apparel and personal styling service company, they find that artificial intelligence-enabled recommendations allow the company to serve the customer with a fundamentally changed value proposition by sending the consumer preselected clothes. The artificial intelligence is internally developed, constitutes the core activity to create revenues and applied in several areas of the value chain (Product design, customer interaction, curation of products, aftermarket), and results in radical innovation of the traditional apparel business model. As a new entrant, however, it is an example of business model design. In a second investigated case, artificial intelligence is used to automatically produce clothes on demand, predict fashion trends and innovate on new styles. The productivity improvements allowing the company to produce on demand have large implications for inventory and encompass the whole value chain activities and represent radical business model innovation and the trend forecasting improve solely one process but can if accurate enough fundamentally change the business model. Also, Amazon is a new entrant in the fashion industry.

Both companies are new entrants with a prior specialisation in tech and artificial intelligence not in the industry they are entering. In this case, it can be assumed that the artificial intelligence capabilities existed before the business model was developed, thus the conceptional business

model design might help explain the dynamic of the artificial intelligence impact. This is especially relevant as in case the business model proves viable, the broader fashion industry will try to imitate it, as has been found above. In that case, business model innovation would directionally lead to artificial intelligence adoption.

In comparison, Garbuio and Lin (2019), find only incremental business model changes of incumbents and complementary services after the market entrance of artificial intelligence-based start-ups, when investigating different healthcare start-ups based on artificial intelligence technology and identifying several different archetypes of business models from the value creation and value delivery perspective. This does not shed light on the mechanism with which artificial intelligence impacts the business model design but provides evidence of how the value is differently created and delivered based on artificial intelligence application. Two main value creation archetypes were identified (1) information provider, which focuses on providing improved information to the patients or doctors including some advice, and (2) Connectors, which focus on value creation via creating connections between patients and doctors or other health service providers. In terms of the value delivery models they commonly employed platform models, and for value capture, Software-as-a-Service or Platform-as-a-Service models were commonly used. Contrary to the common assumption that artificial intelligence introduction into an industry leads to disruption of said industry, the impact of artificial intelligence on the business models, in this case, is extremely low. The start-up's business models investigated are fully complementary to the more traditional healthcare approach. While there is additional support in finding the right specialist via an information provider start-up, the basic business model of the incumbents currently remains the same. This is an interesting example where the artificial intelligence spawned new business models, complementary to the existing incumbent's business models.

The start-ups have a large focus on servitisation, but additionally, it is clear that the current business model in the core industry, which is only using artificial intelligence in some niche applications, was only changed incrementally by improving the parts of the value delivery process, but most of the original processes remain in place. In this example artificial intelligence only affects some aspects of the value chain, mainly focussed on operational improvement and a bit of aftermarket. The incumbents which in some of the cases were the buyers of the start-up services used the artificial intelligence to increase cost efficiency, and the artificial intelligence applications are from the new entrants, and, hence, are externally sourced. It is unclear if further

advancement in the technology may lead to an overhaul of the current health services value chain and could indicate the potential moderating influence of the regulatory environment on the artificial intelligence impact on business models, presumably via the mediating factor of a lowered competitive environment.

This supporting and complementary role of some of the start-ups was confirmed by Aloini et al. (2022) in their case study of the space industry and by Anton et al. (2021) for the electric power industry.

In the space industry, the three start-ups investigated mainly focused on extracting information from satellite images using artificial intelligence. Artificial intelligence here is the core of the operational activity, and in one case impacted the cost model of the company as well. As new entrants, the impact relates again rather to business model design instead of business model change. While the artificial intelligence is internally developed, the data is drawn from an open data source (Copernicus). The new entrants take a supportive, niche role in their industry; the case highlights the importance of considering the data assets together with the artificial intelligence.

In the electric power industry, Anton et al. (2021), found artificial intelligence startups competing with the incumbents and disrupting the market, but also new entrants offering complementary services, only triggering incremental business model innovation in the industry. The artificial intelligence start-ups were active along the whole power value chain from generation to aftermarket service and investment and trading activities. The author identified several business model archetypes from the start-ups and some of the new entrants' business models are complementing the current industry, by providing services such as improved monitoring for maintenance, data analytics, and customer management and, thus, show incremental improvement of the value creation process for the customer, together within the ecosystem of the utility providers and power generating companies. Those artificial intelligence start-ups improve the efficiency of the incumbents but do not bring a major business model innovation and regime change in the industry. There are however some examples of actual disruptive business model innovation showcased by the independent energy supplier archetype, where artificial intelligence is used to offer a different value creation, delivery, and value capture mechanism. The artificial intelligence applications in those start-ups are highly revenue

and growth focussed and are in an enabling role for the business model. Those start-ups could also be viewed as the ones who have the potential to severely disrupt the industry.

The review reveals that new entrants have an important role in introducing artificial intelligence to industries and can disrupt the industries' business models by innovating their business models using artificial intelligence technology. This leads to incumbents aspiring to also innovate their business model radically, and as a result, try to adopt artificial intelligence technologies. Radical business model innovation and disruption are not necessarily the consequence of artificial intelligence-based start-ups entering an industry, as in many cases the new entrants only complement the current industry, resulting solely in incremental business model change for the incumbents. As those findings are based on case studies of specific industries, they cannot be generalised, but this review indicates a similar pattern of interactions and impact in the industries researched.

This clarifies the direction and macro dimensions of business model impact from artificial intelligence adoption, based on the dynamic interaction of new entrants and incumbents in industries and identifies that radical business model change, when proven viable, may lead to a disruption of the industry and its incumbents. Overall, this generates mixed evidence for hypothesis 4, as while the entrance of artificial intelligence-powered newcomers in the industry, can lead to radical change when the core value proposition of the incumbents is successfully fulfilled more efficiently using artificial intelligence, the studies suggest that complementary business models of the newcomers are just as common. This does not allow fully refuting hypothesis 4, but also is no strong evidence in favour, hinting at a more complex relationship than previously assumed. The question is under which circumstances first mover artificial intelligence adoption, impacts the business model radically and when incrementally.

Radical business model innovation has been found by several studies (Chen et al., 2021; Mariani et al., 2023; Xue et al., 2019), but is much less common than incremental change, which is representing the results of most studies (Åström et al., 2022; Björkdahl, 2020; Brooks et al., 2020; Burström et al., 2021; Eling et al., 2022; Garbuio & Lin, 2019; Helm et al., 2022; Kiel et al., 2017; Mariani & Nambisan, 2021; Metzler et al., 2021; Mithas et al., 2022; Viswanadham, 2018; Wamba-Taguimdje et al., 2020; Zheng & Wu, 2017).

4.2 The nature of change of artificial intelligence impact on business models

On a high level, Mariani et al. (2023) found that firms that can fully integrate artificial intelligence in their operating model, i.e. affect several value chain activities, can generate radical business model innovation, changing the business model fundamentally. According to their research, it is enough to only improve one of the three business model dimensions to achieve innovation, but the implementation needs to be fully embraced. For successful business model innovation companies need to build an ecosystem around the new value proposition, interacting with partners and adding complementary products. They theorise that the maturity stage in the industry might have a linkage with the deployment of artificial intelligence to achieve new business models and growth.

In the mature and dispersed market of waste collection in China, collection companies changed the business model by using intelligent collection machines (Artificial intelligence-based) (Xue et al., 2019). The companies employing intelligent collection, changed the value proposition to the consumer, as they can reward the consumer with credit for the recyclables supplied, due to higher efficiencies and shorter value chain approach, cutting out traditional value chain actors such as sorting centres. There also was a revenue model change, adding besides the revenue from trading the recyclable materials, revenues from holding customer credit and receiving some margin on the use of the credit and lastly from customer data sales. The application of artificial intelligence in this case combines several tasks of the value chain into one, changing the dominant business model. As such artificial intelligence affects value chain steps of material inflow (Higher efficiency collection from the consumers) and the operational sorting (Artificial intelligence-based sorting of the materials). Interestingly, in this case, it is not only the amount of value chain activities that are affected, here it is a relatively basic value chain, but rather that the activities of the traditional value chain were also changed in sequence, sorting occurs before the actual collection of the materials. The artificial intelligence capabilities were not developed in-house but by a specialised company also offering the machines. The complementary revenue streams are in line with the literature suggesting the importance of complementary services and products in digital business models. The business model change here is radical, and potentially disruptive, changing the way business has been conducted in the industry, but the technology is not developed internally contrary to this thesis's hypothesis 2. On the other hand, on a global level intelligent collection was already long established and successful before it was applied to the Chinese collection market. In this case, the Chinese intelligent collection companies act as

second-mover in terms of technology but as a first-mover in the respective geographical market. The change is radical and disruptive, and other collection companies adapt by also buying artificial intelligence capabilities. Thus it would give rise to a dynamic that incumbents, when there is a successful artificial intelligence-based business model in their wider industry will experience radical change, even if they did not develop the technology themselves. This suggests a different dynamic of artificial intelligence impact on business models for first movers. There the artificial intelligence development inhouse and across many value chain activities favour radical innovation, while for followers the business model change is fully dependent on the technology developed by the first mover, be it radical or incremental change. It can be proposed that in case the follower has actual internal artificial intelligence capabilities, and the required digitalisation, he might be able to radically innovate in other value chain activities.

Radical innovation by a first mover and incumbent of their industry was researched by Chen et al. (2021). Investigating the servitisation journey of a manufacturing company it was found, that digital servitisation develops in three phases, and changes all three value dimensions. In the first phase, a standard product is produced, and digitalisation mainly used for efficiency gains inside the company. In the second phase, a customised product is developed, requiring extended digitalisation and inclusion of up and downstream supply chain participants to be included in the value creation and delivery considerations. Value capture is ensured by using digital supply chain management to increase the accountability of the supply chain participants. In the last phase, smart products are developed, which require full coordination of a whole ecosystem including partners, outside of the traditional value chain. Digitalisation makes sure efficiencies are created, via coordination, sharing of expertise and advanced product design testing. This article is mainly focused on digitalisation and not on artificial intelligence technologies, but the last stage of development deploys smart products, i.e. products using artificial intelligence. This leads to several takeaways for business model impact and artificial intelligence. Firstly, it clarifies that artificial intelligence needs to be considered concurrently with digitalisation. Artificial intelligence is only the pinnacle of the digitalisation journey and is dependent on having the required data infrastructure and standards, to be able to facilitate large business model changes. Secondly, it highlights the relevance of internal development and expertise in artificial intelligence and digitalisation to pivot an existing business model. Algorithm deployment needs to be second nature to the firm and happen at nearly every step in the whole value chain. Primary deployments may happen for the achievement of efficiency

gains, but major business model impact derives from using it in product innovation, sales and ecosystem integration applications. There is a relationship between using artificial intelligence and the servitisation of business models. All this indicates for companies to radically change their business model when using artificial intelligence, at least two prerequisites are required: Firstly, fully developed digitalisation of their internal value chains, supply chains and their ecosystems, and secondly, expertise and capabilities to develop the artificial intelligence in-house. This is in favour of hypotheses 1 and 2 and extends hypothesis 2 by highlighting the relevance of digitalisation degree and data assets, influencing the impact artificial intelligence has on the business model.

The internal development of artificial intelligence and its overarching effects on the business model were more in-depth investigated in a case study on online review platforms, by Mariani and Nambisan (2021). The research sheds light on two issues regarding the business model change from artificial intelligence. Firstly, they find that companies use artificial intelligence to analyse and predict the customer's preferences for product innovation. This is an interesting application of artificial intelligence in the value chain step of design and development, where artificial intelligence allows to improve the product innovation process leading to a better market fit of the product and more efficient design and market entrance for new products or services. The application of artificial intelligence is, while growth oriented to some degree as the product innovation is a revenue growth topic, mainly efficiency focussed, as the goal is to improve the operational success rate and time to market. Further investigating the topic, the authors find, however, that there are further applications by practitioners. Besides the testing of the product innovation fit, artificial intelligence also is used as a tool to test the business model fit using the same principles. This is a highly relevant consideration for this thesis and adds another dimension to artificial intelligence's impact on business models. In this case, the artificial intelligence is part of the process of new business model design. Without artificial intelligence's predictive abilities new business model adoption would be more difficult and as such the speed of adoption of new business models may be slower, as an industry can only be considered disrupted when there is one player that successfully implemented the business model and by that forces other companies via competitive pressures to also adapt their business models. In this setting, artificial intelligence may be an important factor in the establishment of new business models and the speed thereof. Secondly, this use of artificial intelligence is a very logical next step when the application in the product innovation has yielded positive results for the management. This indicates that the deployment of artificial intelligence in the product

development value chain step may have a positive effect on radical business model innovation. The product development step is generally a point of interest for the application of technology, particularly artificial intelligence, as revenue growth, strategic and top management relevance of this area will necessarily result in contact and understanding of top management for the technology and potentially sparks interest in further applications. It also suggests that there is a high level of digitalisation required for general artificial intelligence adoption, a finding, which is in line with the research of e.g. Chen et al. (2021). The overall argument supports hypotheses 2 and 3, showing the relevance of in-house development and growth orientation.

The connection between artificial intelligence and the degree of digitalisation, particularly the data assets required, was also the main theme of research into a heavy-duty truck manufacturer (Haftor et al., 2021). Radically innovating the business model using digitalisation and in the final stage a machine learning application, it highlights the importance of the underlying data assets, a data network in this case. The artificial intelligence here was developed in-house and used to support an additional offer, that proved to be highly successful in the market. The case was an incumbent in the industry, and highly developed in terms of digitalisation. The player already engaged in customised solutions for its customers beforehand, similarly as suggested by the step-by-step smart solutions journey presented above (Chen et al., 2021), and had already adapted its revenue model from unit sales to renting and leasing models beforehand. The artificial intelligence was used to predict which failure the truck had, based on thousands of sensors inside of the vehicles, which allowed for fast and cheap services and maintenance, and the development of optimised preventive practices and design of better new products. The impacts thus were focussed on the aftermarket part of the value chain but had further-ranging secondary impacts. The artificial intelligence affected the value proposition and cost model. The revenue model was not affected as it already had been adapted beforehand. Even though this business model and new service was a huge success it does not constitute a radical business model change. The business model was already changed before the artificial intelligence was implemented, based on digitalisation and customisation of the company. The artificial intelligence created a large amount of additional value, but only incrementally improved on the previously changed business model components. The business model change was a prior development, that however allowed for the use of artificial intelligence to create more value. It could be assumed that in case the business model had not already changed previously, the artificial intelligence application might have facilitated the change, as the value to created with artificial intelligence would have been higher. This case study also highlights the importance of

data networks as underlying the value creation using artificial intelligence, stating that larger data networks will lead to better artificial intelligence, however, it can be theorised that while a sufficiently large data network is required, larger data amounts will not necessarily constitute better artificial intelligence or greater value creation. This is due to the law of large numbers, stating that at a certain number of observations, the increase in prediction accuracy is relatively decreasing and translates in economic terms into the concept of diminishing marginal returns, considering that the benefit from additional observations in the data network is decreasing while the cost of collecting them remains relatively stable. The company in this case study acted as the first mover in this artificial intelligence application, focused the artificial intelligence use on efficiency and cost reduction and improved the full product life cycle due to a feedback loop from the artificial intelligence results to the product development. As competitors follow this example, the question if this value-creating artificial intelligence capability allows sustainable superior performance remains unanswered.

The research of radical business model innovation converges at three major insights.

Firstly, the impact of one technology on the business model cannot fully be isolated. Most digital technologies and especially artificial intelligence are only making significant radical impacts on business models when they are considered in bundles with other technologies, for example, Internet-of-Things and cloud storage and computing. It is apparent that only a combination of artificial intelligence, processing power and data storage allows for impacts on the business model. Thus, research should be focussing not solely on the impact of one technology but must consider bundles of technologies and required underlying infrastructure. The exact point of change in terms of value creation capture or delivery cannot be identified or tied to a specific technology. The necessity of considering artificial intelligence as part of overall technological advancements and their adaption was confirmed by Viswanadham (2018) when investigating E-retail businesses. Artificial intelligence was identified as a key dimension of competition, as the E-retail business requires fast and dynamic reactions to the market signals, thus efficiency is paramount. However, the impact on business models is not linkable to solely artificial intelligence as there are many technologies enabling E-commerce, emphasising the connection of artificial intelligence with other emerging technologies and digitalisation. In E-commerce artificial intelligence is considered a hygiene factor of competition as in the manufacturing example above.

Secondly, radical artificial intelligence innovation increases the complexity and connection of ecosystem and business partners; a pattern that is found throughout the literature (Chen et al., 2021; Haftor et al., 2021; Mariani et al., 2023; Viswanadham, 2018) and is aligned with the way ecosystem actors in the business model research act together to create the value. This shows that artificial intelligence's impact on the business model strongly relates to and even in some senses extends the effects and impacts of digitalisation on business models.

Thirdly, radical business model innovation based on artificial intelligence has a strong dependency on internal artificial intelligence capabilities in a first-mover scenario, supporting hypothesis 2. Artificial intelligence capabilities allow the company to develop an internal understanding and applications along the whole value chain, and only through internal development artificial intelligence can be fully embraced and lead to radical change in the way business is conducted (Chen et al., 2021; Haftor et al., 2021; Mariani et al., 2023; Mariani & Nambisan, 2021; Viswanadham, 2018). This only partially supports hypothesis 1, as the extent of application along the value chain seems to be a consequence of hypothesis two, indicating a high correlation between the variables.

The importance of the ecosystem alignment for the success of an artificial intelligence-enabled business model change was not only found in radical but also in incremental business model changes as identified by Burström et al. (2021). According to their research, the short-term goal of incumbents with business model innovation is to achieve an ecosystem reconfiguration, while the long-term goal is the revitalisation of the ecosystem. Additionally, they found that artificial intelligence affects the business model, firstly, by forecasting and monitoring, and at later stages by optimising and autonomy. Forecasting and monitoring already are mature and successfully exploited by the sample of the manufacturing firm investigated in this research, while the optimising and autonomy are still in the exploration stage and not yet so far developed. It was further discovered that artificial intelligence functionalities in the manufacturing industry strongly favour developments towards servitisation. The increased information of the manufacturer via Internet-of-Things data and artificial intelligence analytics allows for a risk reduction for the customer and create additional value. Overall, value creation (Better customer understanding, customised solutions and servitisation), delivery (Improved role distribution, improved service experience) and capture (new revenue models) have been impacted by artificial intelligence. Strikingly the authors found that artificial intelligence rarely is only implemented in one functionality but rather in several along the value chain. Artificial

intelligence implementation is viewed by the incumbents as a necessity for competing, therefore artificial intelligence clearly shows growth and revenue focus in this setting. Additionally, the artificial intelligences seem to have been developed internally. All those factors indicate that this should lead to radical business model change, that, however, did not yet take place to the degree that was expected. There are several new revenue models up to full servitisation, but there has not been a full overhaul of the existing business models. One explanation could be that the radical impact would come with the autonomy and optimisation functionalities, which both technologically and practically are not yet developed enough. However, there might also be other factors contributing, such as the type of industry, as especially the manufacturing industry shows a relatively low speed of change (Sjödin et al., 2021). Additionally, while they are creating new offers in their business model the core has not yet changed. The question is if this is the case because the study looked only at a certain period and the development of radical business model change is on its way and will happen eventually or because there is some other roadblock, keeping the industry's business model from pivoting. A factor inhibiting the value capture mechanism with general purpose technologies, according to (Teece, 2018) is, firstly, issues with intellectual property laws and, secondly, low revenue streams from licensing. It is difficult to capture the value created by a technological innovation if you do not have complementary market power. This can be applied to artificial intelligence generally. Secondly. related to the specific industries investigated above (Mining and manufacturing), Teece (2018) argues that in non-consumer markets it is harder to capture the value from an innovation, even if theoretically you hold the monopoly on the innovation, in this case on the artificial intelligence.

Investigations of Internet-of-Things applications in the manufacturing industry mirror the results of Burström et al. (2021), with the authors Kiel et al. (2017) finding that, firstly, new revenue streams were added to the business model via servitisation business lines, and secondly, value creation was affected due to better customer understanding. They also found that in the B2B business, the relationships do not change as strongly, as the classical way of interacting via telephone and email and personal interaction is still prevalent. Those findings are contradicting hypotheses 1 and 2 and show that considering only the technological perspective of artificial intelligence on business model change does not encompass the complex reality of business model innovation, as there are several other factors contributing to the realisation of radical change in the business model, such as the value chain position of the industry and

strategic considerations such as replicability and imitability, summed in the resource based view of Barney (1991).

Another applied artificial intelligence and Internet-of-Things application in the manufacturing sector has been further investigated by Zheng and Wu (2017). Using artificial intelligence it was possible to reduce the inventory required and increase trust between the manufacturer and the suppliers. This showcases once more the importance of open ecosystems for many applications of artificial intelligence and is an incremental improvement of the business model. The application focus of the artificial intelligence is efficiency and cost-reduction oriented, and an example of open innovation as it was developed together with a university. The implementation is located in the value chain at inbound logistics, indicating it is not directly related to the core operations of the firm. Those results fit with hypothesis 3 that cost-focused applications only lead to incremental innovation.

Similar to the results of Burström et al. (2021) and Kiel et al. (2017), Björkdahl (2020) found a trend towards servitisation in manufacturing companies use artificial intelligence in product development for example for software and product design (digital twins), quality control (computer visualisation), supply chain and inventory management, and in preventive, predictive maintenance. However, performance results from the new offering in servitisation have not yet materialised. Machine learning, they find also increased the integration of the value chain; a result that is in line with the findings of Burström et al. (2021) and Kiel et al. (2017). They also discover that digitalisation overall is resulting in more efficiency-based incremental change of processes and growth initiatives are less successful. This finding does not appear to be too surprising considering the higher risks related to market entrance and product launches when compared to solely improving the existing cost structure. The question here is rather if the new growth opportunity success rate is higher when supported by digital transformation than in more traditional market entrances. The conceptual evidence suggests that especially artificial intelligence implementation may lead to higher success rates, as new product testing and customer analysis is possible as described above (Mariani & Nambisan, 2021). Generally, the above-described business model changes are incremental, as the current business model remains fundamentally unchanged at the time of research, supporting hypothesis 3 and, as the majority of artificial intelligence applications are cost-focused, this may indicate that the averaged effect of artificial intelligence is an incremental business model change not radical.

Contrary to those results Metzler et al. (2021) find in a comparative case study of incumbent firms' artificial intelligence application's impact on business model, that cost focussed artificial intelligence application lead to disruptive business model change. The artificial intelligence examples of their research are cost reduction focused but with a disruptive business model impact according to the author's classification. However, investigating the examples of business model change, e.g. automatisation of production processes and artificial intelligence-based after-sales services, it is evident that those changes do not fundamentally change the way business is conducted and are thus incremental business model change, and not disruptive. This highlights the importance of clearly defining the nature of change, as a common misconception is that artificial intelligence necessarily leads to radical and disruptive business models, even though as presented by the papers above the relationship is not causal and is mediated and moderated by several factors. Metzler et al. (2021) further highlight the importance of artificial intelligence partners, by which they mean partners to develop artificial intelligence, such as universities or technology companies with the right capabilities. This fits with for example the need for open innovation propagated by Teece (2018) in digital business models but disregards the crucial role of data networks and ecosystem partners for the actual continuous operation of an artificial intelligence-based offer, product or business model. Nonetheless, the adjusted results fit into the above-proposed impact of artificial intelligence on incumbent firms, also finding that cost reductions are prevalent over revenue increases and that within incumbents of a non-disrupted industry incremental business model change, is the most likely consequence of artificial intelligence introduction not disruptive one and, hence, fit with hypothesis 3.

The insight that artificial intelligence regularly leads to incremental business model change, but other factors besides artificial intelligence-related ones are more relevant (General digitalisation status, data assets, ecosystem integration, maturity of the market, economic and strategical considerations) for radical business model change (Björkdahl, 2020; Burström et al., 2021; Kiel et al., 2017) is also evident in the findings of Wamba-Taguimdje et al. (2020). In their review, they find that artificial intelligence enables the designing of new offerings and organisational processes directly linked within the production processes and can be applied along the whole value chains of firms. The impact is mainly centered around automation, informational and transformational effects at the process level. The first two effects are rather incremental and have less of a growth-oriented perspective while the transformational ones are growth focused in nature and may lead to radical business model change. However, closer investigation of the transformational changes at the process level reveal, that while they impact growth dimensions,

via e.g. forecasting market developments, those process applications do suggest improved offerings and processes, but do not indicate radical business model change. Hence, the study shows that there are incremental changes of the business model in all three value chain areas, but not necessarily a large, radical impact on the business model. They also find that most of their case studies used external artificial intelligence providers to roll out their solutions, such as *IBM* and *CLOUDERA*, an indication that most artificial intelligence use does not come from in-house development but solely from outsourcing. This is a relevant takeaway from the business model perspective and the growth perspective. Firstly, it indicates that organisational learning about artificial intelligence is impaired, as few companies develop their artificial intelligence resources themselves, and thus the understanding of the possibilities of artificial intelligence that are required to be developed by top management to impact the business model to a larger degree, are not given, which fits with results from other studies that artificial intelligence by itself did only have a highly limited impact on their business models and value propositions. Secondly, there is a strategic issue there, as by outsourcing the technology, that may highly impact which products are designed, how they are designed, and priced, constitutes a loss of market power for the user and a gain for the artificial intelligence provider. Similarly, to the manufacturing examples above this highlights the issue, that as the resource to implement artificial intelligence is external, the external provider can offer the same applications to several players in a market, increasing investment costs for the incumbents while not increasing profits, making it a prerequisite to compete while creating no to little value for the company itself. This relates to hypothesis 2 in the opposite direction, indicating that not having artificial intelligence capabilities in-house may strongly encumber the ability to innovate the business model radically.

The artificial intelligence impact on the business model has been so far mainly of incremental nature, with a large focus on improving current practices. The radical business model innovations found were strongly linked to digitalisation, data assets and other factors, such as connectivity of ecosystem actors, in general terms, and could not be traced back to artificial intelligence as a standalone technology. Those results are reinforced by the studies of Eling et al.; Helm et al.; Mithas et al. (2022; 2022; 2022).

Eling et al. (2022) find in the insurance industry, which is highly information-driven, and as such has a high level of digitalisation, that artificial intelligence can be and is applied to multiple value chain activities. Based on those applications the researchers identified two major changes

to the business models of insurance companies. Firstly, the customer interaction, i.e. the value proposition is changed by using chatbots, for customer communication and the creation of new offers and services, secondly cost structure is changed via automation in many areas. The first one relates to revenue growth applications while to latter is an efficiency improvement application. With the insurance industry being highly data-driven in general and many digitalisation efforts, the business models had adapted considerably over the last years with differing degrees of adoption by different companies. This leads to the business model changes from artificial intelligence being incremental, not overthrowing the current paradigm, but improving upon it.

The impact of artificial intelligence on business models in the insurance industry was also investigated by a comparative case study by Helm et al. (2022). Looking specifically at cognitive automation, an artificial intelligence application to extract data points from unstructured sources, in a case study of legacy companies (Insurance, auditing, healthcare and banking), they discovered mainly cost reduction and improved efficiency for the exact task where technology was applied and incremental changes for the business models. This use case investigation, does only focus on the impact of one artificial intelligence application, thus does not investigate the impact of artificial intelligences overall, but in its limited scope the findings align with the results above. Optimisation of one operational activity, outhouse artificial intelligence development, and cost focussed application, only leading to incremental business model innovation in incumbent firms.

The incremental business model improvement due to artificial intelligence application was also found by Mithas et al. (2022). Artificial intelligence implementation impacted operations management via improved decision-making impacting areas such as improved pricing, inventory management, service and aftermarkets mainly via improved or additional information. The artificial intelligence applications focus on efficiency improvements, but there are also revenue improvements via better market intelligence and pricing. Overall, from the operational side, they found that the activities will be changed by artificial intelligence, but mainly efficiency focussed and incrementally, as opposed to radically.

In summary, the research above states that artificial intelligence applications by themselves mainly lead to incremental changes to the business models of companies and artificial intelligence is used to create cost efficiencies, while growth-oriented applications are less

common. The cost improvements do not result in radical but incremental business model changes. This supports hypothesis 3. However, the research shows that artificial intelligence itself and the circumstances of implementation only have a limited impact on radical business model change. For radical business model change to occur many other factors, such as general digitalisation, data assets and strategic considerations may be of higher relevance and act as moderating variables. Artificial intelligence as standalone technology impacts the business model on an incremental level.

4.3 Artificial intelligence impact on business model dimensions

The incremental impact on the business model can occur in different dimensions of the business model, i.e. value creation, delivery or capture, as has been evident in the results above (Anton et al., 2021; Chen et al., 2021; Garbuio & Lin, 2019; Haftor et al., 2021; Silo AI, 2022).

Åström et al. (2022) investigate value creation and capture impacts of artificial intelligence in their case study. In the value creation mechanism, they found that value was created by the company via three areas: Cost efficiencies, revenue growth and business gains. Business gains among others were increased awareness of network actors and refer to non-operational business improvements. Those value creation considerations are supported by the research of Cockburn et al. (2018) who also found that artificial intelligence may create new products and services, as well as facilitate the decision-making process of managers by adding new, previously unavailable or more precise information.

In the value capture dimension, Åström et al. (2022) discovered that value from the artificial intelligences developed in-house can be captured via licensing or output-based pricing, with the first being the better fit, as it opens doors to new potential customers. Nonetheless, this only constitutes one additional offering based on artificial intelligence and does not fully appreciate the value capture mechanism of artificial intelligence in other products, by for example offering a service for maintenance due to Internet-of-Things and artificial intelligence applications using artificial intelligence-based pricing and dynamic contracts. This aspect of artificial intelligence's impact on value capture has been more closely investigated by Agrawal et al. (2019). The perceived value created via a service offering using dynamic pricing is higher when there is transparency between the seller and buyer on the pricing model. This dynamic pricing

model and transparency are enabled by artificial intelligence and lead to the acceptance of higher uncertainty contracts by the buyers in the Nordics manufacturing industry (Agarwal et al., 2022). This indicates that value-based pricing is not only a better option for artificial intelligence-enabled services, as stated by Åström et al. (2022), but also highlights the role of artificial intelligence as an enabler making dynamic and customised value captures acceptable to buyers, which strengthens the perception that only artificial intelligence adoption in several value chain locations allows for radical business model change.

Potential revenue growth from providing pure artificial intelligence solutions is challenging as the value capture mechanism for artificial intelligence solutions themselves is difficult. This does not relate to the integrated artificial intelligence solutions where artificial intelligence is sold as part of a product, but when artificial intelligence is sold as a service or software to different ecosystem partners in its pure form. The issue is the marginal cost for multiplying an artificial intelligence solution is close to zero, but can create large-scale effects in the cost efficiency of processes and revenue improvements, thus instead of a cost-based pricing model, companies selling artificial intelligence technology should consider value-based pricing (Åström et al., 2022). The authors further state that a value-based pricing model for the distribution of value throughout the value network is the most appropriate choice, as otherwise, the true value creation of artificial intelligence is understated.

Offering artificial intelligence solutions does change the value creation and delivery in two ways: Firstly it adds a new offer to its product portfolio and delivers on it similarly to software and tech companies, secondly it has the potential to develop the artificial intelligence and data capabilities of other actors in the value ecosystem, which may be necessary for some artificial intelligence applications and create larger scale business model impact.

Nevertheless, interestingly the result even in this case is an incremental change in the business model. Both the value creation and delivery in the first application are only marginally affected. A new offer is added most likely to the existing product and service palette, from which the artificial intelligence innovation stems in the first place and value delivery and capture are only affected marginally, introducing the use of new activities into the delivery and capturing value most likely with a novel system, be it licensing or output based pricing, but the core business model would remain rather stable.

The second implication of selling artificial intelligence solutions, the further development of the data and digitalisation readiness in the ecosystem on the other hand has potentially a high business model impact as it creates new possibilities for example for fully customised and smart products, as those applications require strong digitalisation along the whole value chain and integration with ecosystem partners. While a full implementation of this type of product leads to large-scale change in all three business model dimensions, it is a complex and incremental process. As such it is rather a step-by-step process, with some discontinuity as is typical for digitalisation efforts, but the resulting business model innovation would not arrive unexpectedly to the industry, even though for some actors it may constitute a full disruption of their business models.

The value delivery dimension is mainly related to the core activities and infrastructure of the firm and as such it is impacted by improvement in the process efficiency. Agrawal et al.'s (2019), results regarding this dimension are in line with our above-stated proposition highlighting that artificial intelligence increases efficiency and reduces costs for existing activities, but do not mention value creation as revenue growth and new business opportunities as impacts.

Considering all the business model dimensions, it remains that most of the artificial intelligence impacts on the business model are rather incremental and small in scope, and not creating industry-wide disruptions. Cost reductions and efficiency do change the value delivery, but do not fundamentally change activities and resources needed but only increase their efficiency. Most of the new products added to the product portfolio are only one part of the business model and constitute a change in the value creation and capture, but as the original products and services remain as a majority of the market share and are potentially only slowly faded out, the change also in this dimension is rather incremental and not radical business model change.

One aspect of increasing importance for business models is their sustainability which is investigated in the sustainability business model literature. This type of business model impact of artificial intelligence does not describe a specific change to the business model itself, but rather an aggregated characteristic of a resulting business model and as such only gives limited insights into the relationship between the artificial intelligence adaption and more specific business model changes.

4.4 Artificial intelligence and sustainable business models

Artificial intelligence-enabled business model innovation can support sustainability via increased productivity, efficiency, i.e. less material used and decreased emissions, and in the public sector make public and health services more broadly available (Di Vaio et al., 2020).

The increased resource efficiency and reduced emission intensity of some artificial intelligence-based business models, particularly with servitisation, were confirmed by the research of Weiss (2019). The additional data from artificial intelligence allows for offering service contracts, in which companies have the interest to keep their product up and running as long as possible, indicating higher sustainability. This research identified additionally that the supply chain can be optimised due to better insights and oversight, which may allow accounting better for footprint indicators. The artificial intelligence applications here do not allow to draw a conclusive inference on the extent of business model impact. The business model sustainability improvement is related to adding a service offering and, thus, is growth-oriented, while the second one is about optimisation, but instead of cost optimisation, it is an optimisation for sustainability impact indicators. The findings indicate that the value chain locations sales and supply chain seem to be especially important for green business model changes, a finding that needs to be confirmed by more empirically based studies.

Those studies generally point towards the potential positive impacts of artificial intelligence on sustainability. Nevertheless, it needs to be remarked that artificial intelligence itself does not necessarily lead to sustainability improvements; taking for example the resource efficiency proposition, higher efficiency can also lead to higher production volumes and result in total a higher resource use. Therefore, it cannot be generally proposed that any application of artificial intelligence and its impact on business models necessarily leads to higher sustainability in the business models. The dynamic is better described by stating that artificial intelligence as technology, enables different business models, that in some situations will lead to improved sustainability. An example would be predictive maintenance, where the company has aligned financial performance with sustainability performance, and the goal is that the product is used as long as possible. In other situations this will not hold as at least in the private sector, financial performance is the main objective of implementing any new technology, and if there would not be external pressures to integrate sustainability considerations into the total performance considerations of the business, via for example carbon pricing and reporting requirements,

artificial intelligence could also be used to the detriment of sustainability. A hypothetical example would be the use of machine learning to correctly time the planned obsolescence of products to not lose customer confidence in the brand. Artificial intelligence allows for optimisation and the optimisation goal may be sustainable, but that is not necessarily the case.

4.5 Summary of key findings of the review

The direction of impact between artificial intelligence and business model is defined by the degree of adoption within the respective market and industry. After a successful introduction of a radical artificial intelligence-based business model change by a first mover, which can be either an incumbent or new entrant, other market incumbents will aspire to also innovate their business model and, thus start artificial intelligence adoption to achieve a certain business model innovation.

While new entrants can spark disruptive changes in the business models of the incumbents, they often only take a complementary role to the offerings of the existing market incumbents, as such there is no clear evidence for hypothesis 4.

Investigating radical business model change due to artificial intelligence, it was found that the impact of artificial intelligence on business models is deeply interwoven with other moderating factors, especially complementary technologies such as the digitalisation degree of the firm, value chain, industry and ecosystem and the availability of data assets. Therefore, it is not possible to isolate artificial intelligence and related variables' impact on radical business model change, but artificial intelligence's impact must be considered together with the impact of digitalisation as a whole and other strategic and processual variables that shape the technological and economic reality of the firm. Nonetheless, while other factors play an equally important role in radical innovation the research suggests that in-house artificial intelligence development and corresponding capabilities have a positive relationship with radical business model change, supporting hypothesis 2. The evidence regarding hypothesis 1 is inconclusive, however, the research indicates a high correlation of broad value chain artificial intelligence adoption to internal artificial intelligence development, which would, in turn, imply an insignificance of broad value chain adoption on the radical business model change, refuting hypothesis 1. This relationship would need to be investigated in further research.

In general, artificial intelligence tends to impact the business model only incrementally, via enhancing the efficiency of the activities, or some revenue and growth gains for the company. Cost focussed applications of artificial intelligence were more common in the literature, compared to revenue focussed ones and mainly led to incremental business model changes, providing evidence in favour of hypothesis 3.

Overall, it has been found that artificial intelligence adoption impacts all the dimensions of the business model. Value delivery is impacted by cost reductions and increased complexity and interconnectedness of the ecosystem, as well as business partners, value creation via new products or services added, improved market intelligence and product development, and value capture via customised pricing and alternative revenue structures, such as servitisation.

The review shows that artificial intelligence's impact on the business model is mainly incremental, but as radical business model change may result in high-stake disruption of the industry it is of utmost importance to gain an understanding of the factors contributing to radical change. Hence, in the following chapter, a conceptual framework for radical business model change and artificial intelligence is developed, based on the evidence presented in the review.

Table 1: Contribution table: Comparison of the selected articles

Author(s)	Company Type	First mover/ follower	Industry or activity type	Internal/External development	Direction of impact	Business model dimension	Nature of innovation
Agarwal et al. (2022)	Incumbent	First mover	Manufacturer	Internal	AI to BM	Value capture	
Agrawal et al. (2019)	Incumbents	Followers	Manufacturing	External		Value capture	Radical
Aloini et al. (2022)	New entrants	First movers	Space industry	Internal	AI to BMI	Value delivery and value creation	Incremental
Anton et al. (2021)	New entrants	First movers	Electric power	External	AI to BMI	Value creation, delivery and capture	Incremental and radical; Complementary and disruptive
Åström et al. (2022)			Telecommunication	Internal	AI to BMI	Value creation, delivery and capture	Incremental
Björkdahl (2020)	Incumbents		Manufacturing	Internal	AI to BM	Value creation and delivery	Incremental
Brooks et al. (2020)	Incumbent	Followers	Legal Services	External	BMI to AI	Value delivery	Incremental
Burström et al. (2021)	Incumbent	Followers	Manufacturing	Internal	BM to AI	Value creation, delivery and capture	Incremental

Author(s)	Company Type	First mover/ follower	Industry or activity type	Internal/External development	Direction of impact	Business model dimension	Nature of innovation
Chen et al. (2021)	Incumbent	First mover	Manufacturing	Internal	AI to BM	Value creation, delivery and capture	Radical
Cockburn et al. (2018)						Value creation	Incrementa
Di Vaio et al. (2020)	Review				BMI to AI	Value creation and delivery	Sustainability
Eling et al. (2022)	Incumbents	First movers	Insurance	Internal	AI to BM	Value creation and delivery	Incremental
Garbuio and Lin (2019)	New entrants	First mover	Health care	Internal	AI to BMI	Value delivery and value creation	Incremental; Complementary
Haftor et al. (2021)	Incumbent	First mover	Automotive manufacturer	Internal	AI to BM	Value creation, delivery and capture	Radical innovation, but AI impact incremental
Helm et al. (2022)	Incumbent	Follower	Insurance, Audit, Healthcare and banking industry	External	AI to BM	Value delivery	Incremental
Iansiti and Lakhani (2020)	New entrants	First movers	Financial services and E retail	Internal	New entrants: AI to BM Incumbents: BMI to AI	Value creation, delivery and capture	Radical

Author(s)	Company Type	First mover/ follower	Industry or activity type	Internal/External development	Direction of impact	Business model dimension	Nature of innovation
Jin and Shin (2020)	New entrants	First mover	Fashion	Internal	AI to BMI	Value creation, delivery and capture	Radical; disruptive
Kiel et al. (2017)	Incumbents		Manufacturing	Internal	AI to BM	Value creation and delivery	Incremental
Mariani et al. (2023)	Review					Value creation, delivery and capture	Radical
Mariani and Nambisan (2021)	Incumbents		Diverse with online review and testing platforms	Internal	AI to BM	Value creation and delivery	Incremental
Metzler et al. (2021)	Incumbents	First mover	Automotive, Pharmaceutics, Industrial products, Consumer & Retail	Open innovation and internal	AI to BMI	Value delivery	Incremental
Mithas et al. (2022)	Incumbent	Follower	Manufacturing			Value creation	Incremental
Sena and Nocker (2021)	Incumbent and new entrants	First mover and followers			BMI to Ai	Value creation, delivery and capture focussed	Radical; disruptive
Sjödin et al. (2021)	Incumbents		Manufacturing, shipping, construction and mining	Internal	BMI to AI	Value creation, delivery and capture focussed	Radical

Author(s)	Company Type	First mover/ follower	Industry or activity type	Internal/External development	Direction of impact	Business model dimension	Nature of innovation
Viswanadham (2018)	New entrants and incumbents	First movers	Retail	Internal		Value creation, delivery and capture	Incremental
Wamba-Taguimdje et al. (2020)	Incumbent		Diverse	External	AI to BM	Value delivery and value creation	Incremental
Weiss (2019)	Review						Sustainability
Xue et al. (2019)	New entrants	Followers	Waste collection	External	AI to BM	Value creation, delivery and capture focussed	Radical
Zheng and Wu (2017)	Incumbents	First mover	Manufacturing	Open innovation	AI to BM	Value delivery	Incremental

5 Towards a framework of artificial intelligence and business model change

There is one main similarity between any artificial intelligence impact on the different business model components. Any artificial intelligence for any usage is based on underlying training data. At the current technological state, artificial intelligences need to be trained and configured to a specific task or purpose, using data, even though it may be later possible to transfer it to other applications. Artificial intelligence viewed from this perspective is the pinnacle of data-driven organisations and processes, requiring a large-scale digital transformation to have taken place prior, as is also suggested by the results of the review. The connection between the data assets and the artificial intelligence possibilities is a causal one, i.e. the available data will define what the artificial intelligence can do and which parts of the business model it will impact.

Artificial intelligence can impact value creation and delivery by creating new value propositions, such as new services or products, but also impact value delivery by improving supply chain coordination, increasing efficiency in internal processes, and reducing waste. The value capture can be impacted by customised pricing, e.g. artificial intelligence-tested pricing models. However, the value capture process is not purely technology dependent. It is stronger dependent on the power structure within the value ecosystem, with the player controlling the major bottleneck resource or capability exerting disproportionate power and capturing larger shares of the value (Teece, 2010). In the artificial intelligence case, if there are not any other major constraints in the value ecosystem, this is either the artificial intelligence itself or the required data assets. The artificial intelligence itself is a general-purpose technology (Magistretti et al., 2019) and as such it can be relatively easily replicated for any specific application, even though it may take effort and some development time, the technology is generally not the main limiting criteria. This leaves the underlying data assets as the major scarce strategic resource considering artificial intelligence application and business model impact.

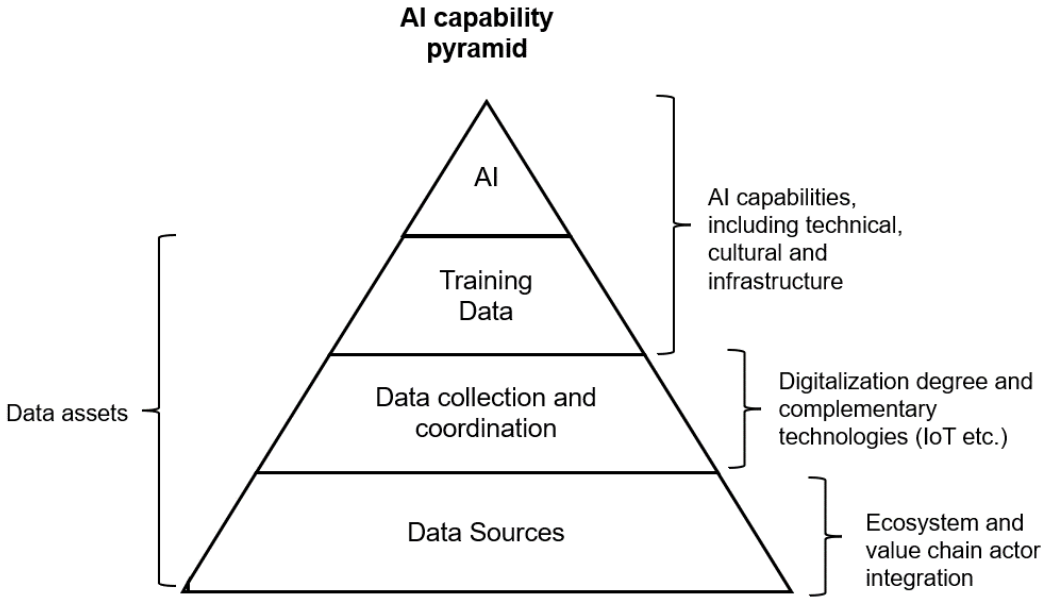

Figure 2: Artificial intelligence capability pyramid

Source: Author's own illustration

An artificial intelligence application can impact value creation in a way that allows to derive additional value from the same input, e.g. by increasing the useful life of an asset in case of predictive maintenance, and potentially make the delivery of the value possible as well, e.g. predicting the maintenance needs of the respective asset. For a given value creation and delivery change in the business model, the value capture is the most interesting part, as it indicates how much value the company can extract from their artificial intelligence application. The digital and smart economy is riddled with examples of small companies upending large incumbent firms but struggling to turn a profit on the large revenues they captured, with one prominent example being Uber. On the other hand, there are large incumbent firms, that adopted artificial intelligences along their value chain, for example, the case study of Chen et al. (2021) from above, and turn a healthy profit margin in an otherwise contested market. Both examples use artificial intelligence to create and deliver value differently to the consumer than was done before, but there is a difference in the value capture. Interestingly Uber uses artificial intelligence even for customised pricing, i.e. optimises even value capture with artificial intelligence, but still, it has trouble capturing the tremendous value it creates. This is a result of the dynamic described above. The value capture in the business model is not primarily dependent on the exact technology or pricing model applied but on the amount of market power, each player has in the respective value ecosystem. The problem with artificial intelligence is,

that it is easily replicable, and if the data assets that form the base are also simple, this leads to huge value creation, but no market power to capture the value, no matter how sophisticated the value capture mechanism itself is. But what then differentiates successful artificial intelligence implementation and a failed value capture? The major difference is in the complexity of the underlying data assets required. Uber creates huge value and delivers it with the highest efficiency possible but struggles at capturing that value and the result is a price decrease for the customer. The data assets required for Uber to train its artificial intelligence are extremely simple, consisting, in its most basic configuration, of the location data of the driver and the customer. Each of those two data sources (Customer and driver), would need to only provide one data point to train an artificial intelligence to match demand and supply and build a prediction model for demand over time. This type of data asset can be termed shallow and simple. In the case study of Chen et al. (2021) on the other hand, the company had to embark on a decade-long digitalisation process, first internally, then along its supply chain and in the last stage with its ecosystem partners, to create new products and services using artificial intelligence and Internet-of-Things technologies, because the data assets required to deliver those artificial intelligence solutions are extremely complex. There are countless different data sources required, with every source consisting of many data points (e.g. Customer specifications, usage behaviour, the supplier's production capabilities and the connection points with ecosystem partners to create an integrated solution) with all actors and sources requiring coordination. The resulting data needs to be brought into workable formats and transmitted to the studied company to create a smart and customised solution using artificial intelligence. The data in this case is highly complex and deep, meaning large amounts of different sources, different formats, and many data points per source. This data complexity requires the coordination of many actors in the value ecosystem and strong digital capabilities of each. The capability that the studied company demonstrates is highly complex, and as such ambiguous, creating a core competency (Barney, 1991; Grant, 1991). However, as it also requires inputs and cooperation from other actors, the incentive is to distribute the new value created among the different ecosystem actors sustainably and engage with those actors to improve their internal processes' digitalisation and use of artificial intelligence.

The complexity of the underlying data assets is defining the amount of value that can be captured by the value chain. Shallow and simple data assets as the basis for the artificial intelligence potentially will lead to lower overall value capture due to low sustainability and high transferability and resulting competitive pressures, while highly complex and deep data

assets lead to a substantial value capture by the ecosystem. This is all mitigated to some extent by other factors such as regulations and other core competencies required in the ecosystem but when investigating the impact of artificial intelligence this is a main takeaway.

This has practical and theoretical implications. The theoretical implication is that in line with Barney's (1991) resources and capabilities theory, for artificial intelligence application, data assets and their respective complexity constitute a core competency. The impact on business models depends greatly on this data complexity, as, firstly, the change to all three dimensions, value creation, delivery and capture, is different in nature. Low data complexity, simple and shallow data assets and high value creation and efficient delivery will lead to radical and disruptive change in business models of a whole industry, fully changing the way business has been conducted and will most likely be brought about by new entrants. High complex data assets as the basis for the artificial intelligence lead to slower and step by step, incremental adjustments of the business model, slowly changing the value creation and delivery and changing the value capture to favour customised models, such as pay-per-use and servitisation. This change process takes more time and is likely to benefit the whole value ecosystem. Those impacts may be adjusted upwards and downwards, depending on the closeness to the end consumer (use of lock-in effects and brand loyalty) and other macro factors such as the degree of regulation of the industry, the basic dynamic, nevertheless, remains the same.

On the practical part, it indicates an important managerial task, that is in the end the exercising of a dynamic capability (Teece, 2007). Companies' management must, if hoping to perform superiorly in the long run, look at their whole value creation ecosystem and its existing or creatable data assets, consider where artificial intelligence technology may create value via new services and products and ensure artificial intelligence and their digital capabilities can deliver on that value proposition. In the next step, they need to anticipate if the data assets required to develop the artificial intelligence solution are deep or shallow. In the case, there is little value creation, and the data assets are simple, it might be a good option to let external parties with expertise in artificial intelligence enter the market and provide the solutions for a specific task in the value chain. When the data assets are complex, and value creation low, the investment is likely too high and not feasible. Here, however, it is necessary to also consider the second-degree effects of learning new capabilities. If the data asset is shallow and huge value created, like in the case of Uber, incumbents must ensure to gain the required capabilities and prepare a roll-out of the technology and respective complemental offerings to ensure that they still can

capture some amount of value, when the disruption eventually takes place. Lastly when there is high data complexity and value creation of artificial intelligence applications, long-term investment in the data assets, artificial intelligence and analytical capabilities is necessary, and allows to build a high value capturing ecosystem, offering a long-term sustainable growth path using artificial intelligence. In any case, in-house artificial intelligence capabilities and understanding are of vital importance to any company, that can afford to build them, as they constitute the minimum requirement to sense, anticipate and react to a potentially disruptive change in their industry. The minimum is understanding artificial intelligence from a high-level manager's perspective, as in that case anticipation is possible and makes sure there is no feasible application opportunity, which may upend the company's business model. Especially for cost improvement, artificial intelligence may also be sourced externally without any effect on the other business model components, but in case of revenue growth applications, internal development is a must as only through it, it is possible to create new products and services and change the value creation and capture of the firm in the long run.

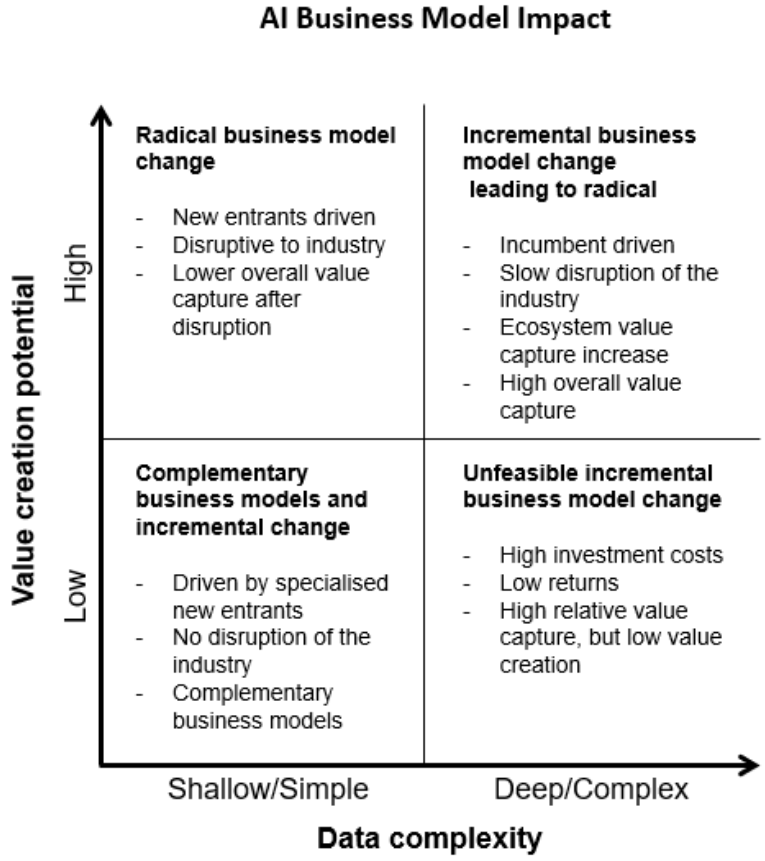

Figure 3: Artificial Intelligence's business model impact

Source: Author's own illustration

6 Discussion

The review above has shown that the artificial intelligence and digitalisation are interconnected, and artificial intelligence is building on digitalisation, more particularly the data assets and infrastructure generated by the digitalisation. Data driven business models, e.g. data driven servitisation, is an advanced step of digitalisation (Kohtamäki et al., 2022). Artificial intelligence is a specific form of data analytics, more specifically predictive analytics and as such the business model impact of artificial intelligence is related to the impact of digitalisation on the business model.

This is demonstrated for example by Westerman et al. (2014, pp. 78–92), who identify five general archetypes of business model change, on different levels. Digital technology may (1) reshape industries, (2) substitution of existing products with digital one, (3) creation of new markets, (4) improving the value delivery and (5) creating new products and services to match unserved customer needs. In the review above it was found that in some circumstances artificial intelligence can reshape markets, by disrupting the incumbents, substitute products, for example predictive maintenance instead normal maintenance, create new markets, as showcased by the new artificial intelligence based entrants in the health care industry, improving the value delivery via automisation of processes and improving of efficiencies, and lastly the creation of new services and products, for example fully customised smart solutions. All those archetypes of digitalisation business model change have been identified in research on artificial intelligence and business model change. This indicates strong alignment of the impact of digitalisation on the business model and artificial intelligence on the business model and emphasises the importance of considering artificial intelligence as a digital technology based on digitalisation.

6.1 The nature and direction of business model change

Similar to the findings of artificial intelligence's impact on business model innovation, Rusch et al. (2023) found that incremental innovation is predominant in digital transformation, while radical innovation is less common. The similarities between the artificial intelligence and the digitalisation impact extend beyond the predominant type of innovation being incremental, to also the mechanism leading to incremental and radical business model changes.

6.1.1 Business model innovation internal and external triggers

Frank et al. (2019) do not investigate artificial intelligence but investigate the level of digitalisation and its effect on servitisation including predictive analytics as a part of the digitalisation process. They found that in a technology push scenario, where the company has high levels of digitalisation, internal gains in efficiency and quality can be observed as a result which suggest incremental change of business model. In a scenario with a low digitalisation and high servitisation level demand pull is responsible for increased servitization. This is in line with the review findings on artificial intelligence induced efficiency gains, not leading to strong servitisation (radical business model innovation) and indicates as suggested in the framework that in case of incumbent development of the digitalisation without demand pull the business model change would be less radical, as was also found for artificial intelligence. An open question with digitalisation and particularly artificial intelligence is, if there are factors that may lead to radical business model change in the incumbent firms when the technology is ready, or if without external influences incumbents would never innovate radically but only incrementally.

This low probability of incumbents to function as disruptors of their industry when using technology, is not only present with artificial intelligence but also in the digitalisation business model literature. Incumbents tend to use the digitalisation to develop their business model step by step, evolutionary instead of radically and disruptive (Cavalcante et al., 2011; Foss & Saebi, 2018; Kim & Min, 2015). This finding is consistent with our findings for artificial intelligence adoption and business model change, showing that incumbents tend to evolutionary incremental changes to their business models instead of radical ones. That digitalisation does not necessarily lead to disruption and radical business model innovation has also found by Rachinger et al. (2019) when investigating the industries of media and automotive. Alike the review results for artificial intelligence they identified that digitalisation did not lead to a disruption, but they found incremental process optimisation and revenue increases as results of the digitalisation process.

The dynamic of internal pressure and external push for change in business models is not only present in the literature on digitalisation and servitisation (Frank et al., 2019) but also investigated for business model innovation generally. Bucherer et al. (2012) find five dimensions that link business model innovation: Origins of the innovation, innovation process,

organisational implementation and anchoring, as well as degree of innovativeness. In alignment to the results related to the origin of artificial intelligence, they found that business model innovation can be triggered externally, via external opportunity, called market pull by Frank et al. (2019) and external threats, where threats represent external entrants. This dynamic was also evident in the artificial intelligence business model relation when an artificial intelligence based market entrance forces the incumbents to adapt to the innovation. One of the overarching factors leading to business model change, identified in business model innovation literature is technological change, which artificial intelligence can be subsumed in. Besides the external triggers for business model innovation internal dynamics can also lead to innovation. The innovation can be either triggered by internal opportunities, when internal research and development discovered for example a technological innovation, or via internal threat. Internal opportunity could be an incumbent's artificial intelligence adoption and the consequent creation of new products and services in the market or improvement of their processes. Those findings are in line with the results of the review in terms of the direction of change, i.e. internal development as first mover leads to business model changes and external pull factors, adoption by competitors or new entrants, pulls the incumbent to adopt the new technology to achieve business model innovation.

It has also been evident that the digitalisation in incumbents often leads to slower and more incremental business model changes, or is generally incumbered, resulting in the eventual disruption of the industry. This dynamic is not only evident in artificial intelligence adoption but also in digitalisation. Chesbrough (2010) identifies two barriers to business model change. Firstly, top management, even if knowing how the business model needs to be adapted to fit the technological innovation, have little incentive to invest in the change as the resulting business models tend to have lower margins than the original ones. When failing to adapt, however, they may be disrupted without any preparation leading to the demise of the respective incumbents (Amit & Zott, 2001). It is highlighted that the technology itself does not need to be complex, but when combined with a fitting business model the result can be the disruption of the incumbents. Secondly Chesbrough (2010) argues that the existing business model's logic acts as a barrier, as only the market signals are considered that fit the existing model and thus information that would be relevant to find the optimal business model fit is disregarded. Consequently, the firm experiences a cognitive barrier, failing to discover which business model would fit the new technology well.

Those barriers were also identified by Weill and Woerner (2015). As was suggested in the review of artificial intelligence the notion that young and new companies (new entrants) are more likely to strongly adapt their business model is evident in their research on digital business model change, as incumbents are hindered by cognitive and economic path dependencies, based on knowledge and work silos, legacy systems, global activities and organisational complexities.

6.1.2 Overcoming business model change barriers for incumbents

The business model innovation literature suggests overcoming this issue by mapping the business model conceptionally to explicate the value logic of the firm and understand how the technology affects the business model as well as, changes to the business model will manifest (Osterwalder, 2004). This indicates that while this review was solely focussed on understanding artificial intelligence, succeeding with a business model innovation based on artificial intelligence does additionally require a solid understanding of the existing business model logic to allow management to anticipate valuable artificial intelligence applications.

Mapping the business model, however, does not directly lead to changes in the business model. Business model innovation research suggests, that experimentation can be used to reconfigure the business model, like in product testing. Here, as described above, artificial intelligence impact may improve the efficiency of this task substantially as, for instance, simulations of business model innovation results can be used to accelerate innovation (Mariani & Nambisan, 2021). Thus, artificial intelligence may increase the speed of innovation overall, e.g. product innovation, other technologies and business model innovation, increasing the number of necessary business model adjustments. The accelerating effect of technology on business model innovation and its feedback loops has also been indicated in the business model literature (Rachinger et al., 2019).

Business model innovation barriers can, at times, only be overcome via effectuation, which in comparison to experimenting, where careful testing is conducted in a controlled setting, is acting and affecting the environment to gain new information on the viability of a business model. This can be particularly effective to challenge the logic of the existing business model. Both business model experimentation and effectuation require a responsible person to lead efforts and support an eventual roll-out (Chesbrough, 2010). Business model change is mainly within the authority and responsibility of top management (Bucherer et al., 2012), which relates

to the finding, that management understanding is essential for artificial intelligence to enable for radical business model changes.

In general, it can be stated, that incumbents and new entrants react to the adoption of a new technology with different types of business model innovations (incremental or radical) and speed, in line with the results for artificial intelligence adoption.

6.1.3 Business model innovation for new entrants

Investigating the business model innovation literature and entrepreneurship, it is evident that for entrepreneurs business model design is viewed as an open playground and sandbox for experimentation, with the goal of maximising the value capture (Filser et al., 2021). This contrasts with the business model innovation dynamics for incumbents as identified by Chesbrough (2010) validating the found difference in terms of business model adoption of incumbents in regard to artificial intelligence.

For new entrants and entrepreneurs, the dynamic is depending on the business model design. The business model design process is defined by experimentation and iteration, with prototyping and piloting being common. Business model design occurs faster if it is opportunity driven. It is a chaotic and non-linear process, well suited to the dynamic structure and trial and error culture of start-ups and new entrants (Bucherer et al., 2012). This insight shows that new entrants will adapt faster, manage the experimentation and iteration processes better and can quickly change their business model compared to incumbents, thus presenting favourable conditions for radical business model change. This may potentially lead to the disruption of the incumbents, whose business model innovation processes are hindered by the above-mentioned barriers. Those general business model innovation and design dynamics explain the findings of differences between artificial intelligence adoption impact in incumbents and new entrants and, hence, are aligned with the general framework for artificial intelligence and business model adoption.

In incumbents creating a separate organisational unit for experimentation with business models may lead to more radical change, but this may still be limited, as the new business unit may pose a cannibalisation threat to the existing business models and missing management support

and knowledge (Bucherer et al., 2012). Missing management support can be remedied by a top management sponsor for change.

6.1.4 Management support as mediator

This highlights the importance of the management support as a factor for radical business model innovation, as was also proposed as mediating variable for the artificial intelligence and business model relation and is linked to the inhouse or outhouse development of technology. The link of management support to internal and external development is likewise found in the digital business model innovation literature (El Sawy et al., 2020), stating that without digitalisation experience senior leadership poses a barrier to business model transformation. Bouchikhi and Kimberly (2003) find that senior leadership fails to realise radical business model innovation opportunities if they are not able to disregard the existing business model's logic. Those findings align with the impact of artificial intelligence understanding and inhouse development on the nature of business model change, indicating that without prior experience of artificial intelligence use, the company is unable to apply it in a pivoting way.

The relevance of management support is evident in literature predating the introduction of the business model concept, stating that top management support for implementing new market orientations is crucial (Narver & Slater, 1990) and is further confirmed by Sabin and Glovatchi (2021) also finding that leadership support and organisation culture are highly relevant factors in facilitating business model innovation with Internet-of-Things solutions.

6.2 Business model innovation and strategic considerations

Like in the artificial intelligence results, the more general literature identified technology as an enabler for business model innovation (Filser et al., 2021) and emphasised that there are other underlying fundamental factors, such as business model design and the relationship between business model and strategy strongly impacting the business model changes.

As with artificial intelligence, regarding digitalisation the importance of big data and business model innovation is highlighted by Sorescu (2017), showing that big data from internal sources can be used to create a better product. This can be done using internal analytics, or if the

capabilities are missing, data analytics can be outsourced to third party providers (IBM, Microsoft), selling analytics capabilities as a service. Openly available external data could even be used to create a purely information- services based business model. This contribution's results relate to the findings of this review, by suggesting the use of internal data to develop new revenues and increase customer understanding or selling the analytical capabilities to other players to create additional value.

However, even though technology may improve efficiencies and enable business models that create more value than prior possible, the firms applying the technology might not be able to capture the value. As stated regarding incumbents above, technology enabled business models do not necessarily lead to improved returns. This is also found on a more generalised level by Chesbrough and Rosenbloom (2002) and Gebauer et al. (2020).

Chesbrough and Rosenbloom (2002) argue that the value of the technology can only be captured if business model fit to the technology is given. Amit and Zott (2001) found that four key value drivers affect value capture in e businesses: Efficiency, novelty, lock-in effect, complementaries (bundeling), showing that technology by itself is not sufficient as a differentiator to achieve value capture. Other mechanisms need to be applied to derive value from innovation adoption. Gebauer et al. (2020) also find that when digitalisation is applied companies are often unable to earn the expected revenues from their investments in digital offerings. All this supports the proposition that artificial intelligence adoption by itself rarely will lead to improved value capture for the company but that there are other mechanisms at work as well. The ecosystem value capture, especially relevant for artificial intelligence based on complex data assets, for example can be impaired by a collaboration barrier, as mutual trust between the ecosystem actors is required. Overall, as suggested in the artificial intelligence framework, it is necessary to ensure fit between the business model and artificial intelligence application to capture artificial intelligence value.

The dynamic capability dimensions of the business model innovation is not only proposed in the framework above, but also widely found in general business model innovation literature (Filser et al., 2021) but it needs to be emphasised that it is also evident that dynamic capabilities in regard to one technology only relate to a specific business model innovation ability. This capability to successfully navigate the business model change of one technology is a part of the dynamic capabilities. However, this capability is technology specific and does not represent

everything dynamic capabilities constitute, and as such, is not equal to a fully developed dynamic capability.

7 Directions for further research

This review has been able to consolidate the existing literature on the business model impact of artificial intelligence adoption and as a result identified gaps in the existing research. Overall, it has been evident that the majority of the studies on artificial intelligence and business model impact have been single case studies or comparative case studies but no large-scale quantitative research has been conducted until this point, which results in limited generalisability of the results and many of the inferences of this review will require validation with larger quantitative studies.

7.1 Definition of artificial intelligence-based business models

The definition of what constitutes an artificial intelligence driven business and business model is fuzzy in current literature and this review avoided this issue by only considering artificial intelligence applications in the primary value chain activities. However, it needs to be investigated if support activities applications of artificial intelligence may in fact trigger business model change processes.

> *Can artificial intelligence use in the support activities impact the business logic of the company?*

7.2 Artificial intelligence and digitalisation

It has been shown that artificial intelligence and digitalisation are strongly connected and have similar impacts on the business model and need to be considered in bundle.

> *How do different levels of digitalisation and artificial intelligence adoption interact with each other in regard to business model innovation?*

Does artificial intelligence capability development necessarily require prior development of strong digitalisation capabilities? I.e., is there a path dependency of artificial intelligence on digitalisation?

Does top management that was exposed to digital transformation processes and data driven decision making perform better adopting artificial intelligence in their activities?

7.3 The nature of artificial intelligence's business model impact

Further this review found a strong distinction between first mover artificial intelligence adoption, and follower adoption as well as between the incumbent and new entrant adoptions. This literature review found that incumbents strongly tend to incremental business model innovation even if they are first movers, hence it needs to be investigated when artificial intelligence adoption of an incumbent would lead to radical change.

Under which circumstances does artificial intelligence adoption of an incumbent lead to radical and when to incremental business model change?

The expectation in this review was that new artificial intelligence-based entrants would lead to radical business model innovation and disruption of the industry. Contrary it was found that new entrants often only create complementary offerings. The offered explanatory variable proposed by this review is training data complexity but needs to be confirmed by empirical research.

When does a new entrant's technological innovation result in disruption of existing business models of an industry and what favours complementary offerings?

Artificial intelligence has been commonly used in product innovation and the creation of new services. The current literature did not investigate if the revenue opportunity based on artificial intelligence have resulted in higher success rates of market entrance and consequent better performance compared to non-artificial intelligence-based production innovations.

Are artificial intelligence-based growth opportunities more likely to succeed in the market compared to non-artificial intelligence based initiatives?

The way of artificial intelligence adoption (Internal/external development, specific value chain location) has been found to be relevant by this review. As the review is based on a limited number of studies none of which investigate the topic directly, this finding should be confirmed by additional research. Thus, further research in different industries is needed for the following topics.

What is the effect of internal artificial intelligence capabilities compared to third party sourced artificial intelligence on the business model innovation?

Do internal artificial intelligence capabilities favour artificial intelligence adoption in multiple value chain activities?

Does artificial intelligence in the front-end activities lead to more growth focussed business model innovation compared to other artificial intelligence applications?

Are companies who are using artificial intelligence by themselves more likely to develop a (management) culture open for new artificial intelligence applications?

7.4 The strategic dimension of artificial intelligence and business model innovation

Considering the broader strategic implications of artificial intelligence, and its classification as a general purpose technology, this review suggests that artificial intelligence rarely represent a core competency by itself. This finding should be investigated in more detail.

Can ownership of artificial intelligence itself result in market power, or does market power necessarily require the combination of data assets and complementary capabilities with artificial intelligence?

The data component of artificial intelligence has been used in the literature to suggest data network effects of scale. This assumption is made in analogy to platform network effects, it is

however unclear if there may be a maximum data size for artificial intelligence applications leading to diminishing returns for businesses.

> *Is there a maximum size of training data after which the improvement of the artificial intelligence is marginal declining and non-value creating?*

Further it was identified that in some ecosystems one actor with artificial intelligence capabilities acts as artificial intelligence vendor and trainer for the other participants. It needs to be investigated in more detail under which circumstances a company will share its artificial intelligence capabilities with other ecosystem actors.

> *Under which circumstances will a company with developed artificial intelligence capabilities share the knowledge with other ecosystem actors?*

Relating to the same area of research, artificial intelligence applications can require a broad range of data sources and as a result companies need to participate in ecosystems. The exact effect of ecosystems on the value capture component of business model in combination with artificial intelligence requires clarification.

> *Does artificial intelligence adoption create more value for actors in a highly digitalised ecosystem?*

This review finds that the value capture from artificial intelligence enabled business models is dependent on the data complexity. This finding is based on case study results and needs to be investigated on a larger scale and with different industries.

> *Does higher complexity of the data assets allow to capture higher value for artificial intelligence-based businesses?*

> *Which factors overshadow and moderate the impact of data complexity in combination with artificial intelligence on business model change?*

8 Conclusion

This review has investigated the impact of artificial intelligence on business models and found that the effect of artificial intelligence on business model change is strongly interlinked with the effects of digitalisation and other technologies and cannot be sufficiently isolated. However, it has been proposed that the underlying data asset's complexity defines the amount of value the business can capture. Artificial intelligence changes the business model predominantly incrementally, with new entrants at times radically innovating the business model and disrupting an industry. Artificial intelligence's impact on business models extends some of the impacts of digitalisation. This research adds value by providing a holistic evaluation and consolidating the literature on artificial intelligence and business models. It identifies different dynamics of artificial intelligence adoption’s business model impact on incumbents and new entrants and proposes a framework for understanding and anticipating industry disruption based on artificial intelligence. This framework should be helpful for the academic community to identify new research areas and organise the existing literature and for management to better understand artificial intelligence's implications for their activities and business models, providing them with the tools to identify opportunities and threats arising from artificial intelligence. This research is limited, as it is a literature review, and many of the articles included were case studies, which makes the overall insights less reliable as the case studies do not allow for generalisability. This limitation can be remedied by conducting broader and large-scale empirical research in different industries in the future.

Furthermore, this review gathered its articles mainly from Business Source Complete, which may have disregarded some relevant articles outside this database. This issue should be mitigated by adding articles using the snowball method. This risk can, however, not be entirely eliminated. Further in the review, grey papers and practitioners' contributions have been neglected. The widespread usage of the search terms artificial intelligence and business model would have resulted in a high volume of mainly non-relevant articles and overshot the scope of this thesis. Future research could use a bibliometric approach to consolidate this literature stream.

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10 Appendix

Content follows on the next page.

Appendix 1: Snowball method selection

Author, editor or organisation	Year derived	DOI name	Inclusion final	Exclusion Reason
Agrawal, Ajay; Gans, Joshua S.; Goldfarb, Avi	2019	10.1257/jep.33.2.31	TRUE	
Anton, Eduard; Oesterreich, Thuy Duong; Schuir, Julian; Protz, Leslie; Teuteberg, Frank	2021	10.1142/S0219877021500048	TRUE	
Armour, John; Sako, Mari	2020	10.1093/jpg/joaa001	FALSE	Mostly hypothetical considerations of potential business models in the legal sector based on AI. Not really data-based research and no methodology on research strategy etc.
Åström, Josef; Reim, Wiebke; Parida, Vinit	2022	10.1007/s11846-022-00521-z	TRUE	
Björkdahl, Joakim	2020	10.1177/0008125620920349	TRUE	
Chen, Yihua; Visnjic, Ivanka; Parida, Vinit; Zhang, Zhengang	2021	10.1108/IJOPM-08-2020-0544	TRUE	
CHOI, J. PILA.Y.; FERSHTMAN, CHAIM; GANDAL, NEIL	2010	10.1111/j.1467-6451.2010.00435.x	FALSE	Not relevant in terms of actual content, with no AI or BM.
Cockburn, Iain; Henderson, Rebecca; Stern, Scott	2018	10.3386/w24449	TRUE	
Davenport, Thomas H.; Dreyer, Keith J.	2018		FALSE	Not scientific, no methodology.

Davenport, Thomas H.; Ronanki, Rajeev	2018		FALSE	Not scientific, no methodology.
Fukawa, Nobuyuki; Zhang, Yanzhi; Erevelles, Sunil	2021	10.3390/joitmc7030175	FALSE	Not relevant in terms of actual content, with no AI or BM.
Gauthier, Caroline; Bastianutti, Julie; Haggège, Meyer	2018	10.1002/jsc.2192	FALSE	Not relevant in terms of actual content, no AI.
Hoffman, Reid	2016		FALSE	Only focussing on potential applications. Nicely structured and fairly interesting but not scientific and or relevant for RQ.
Iansiti, M.; Lakhani, R. K.	2020		TRUE	
Kiel, Daniel; Arnold, Christian; Voigt, Kai-Ingo	2017	10.1016/j.technovation.2017.09.003	TRUE	
Kolbjørnsrud, Vegard; Amico, Richard; Thomas, Robert J.	2016		FALSE	Non-Scientific missing relationship to the business model.
Kotarba, Marcin	2018	10.2478/fman-2018-0011	FALSE	Not related to AI.
Kuzey, Cemil; Uyar, Ali; Delen, Dursun	2014	10.1016/j.dss.2013.11.001	FALSE	Not relevant; Using machine learning, not investigating it.
Mariani, Marcello M.; Nambisan, Satish	2021	10.1016/j.techfore.2021.121009	TRUE	
Matzkevich, Izhar; Abramson, Bruce	1995		FALSE	No business model relation.
Mishra, Shrutika; Tripathi, A. R.	2021	10.1186/s13731-021-00157-5	FALSE	Mistakes in writing, unclear use of synonyms, Untrustworthy work. Excluded
Ng, A.	2016		FALSE	Unscientific work, missing methodology.
Plastino, Eduardo; Purdy, Mark	2018	10.1108/SL-11-2017-0106	FALSE	Unscientific work, missing methodology.

Ransbotham, Sam; Kiron, David; Gerbert, Philipp; Reeves, Martin	2017		FALSE	Unscientific work, missing methodology.
Sena, Vania; Nocker, Manuela	2021	10.1561/0200000100	TRUE	
Spil, Ton; Kijl, Björn; Salmela, Hannu	2016		FALSE	Weak methodology, unclear citing, Low quality of academic work.
Tyagi, Kalpana	2020	10.1108/JBS-10-2018-0173	FALSE	Effects of digitalisation and business model innovation on the market concentration; Not directly related to the business model and AI.
Wang, Quan; Li, Beibei; Singh, Param Vir	2018	10.1287/isre.2017.0735	FALSE	Model building, non-implemented model.
Weiss, Pablo	2019		TRUE	
Wilson, H. James; Daugherty, Paul; Bianzino, Nicola	2017		FALSE	hypothetical jobs AI may create. Purely a conceptual and hypothetical paper. It could be cited for the discussion of the human skill part.
Zhou, Li; Chong, Alain Y.L.; Ngai, Eric W.T.	2015	10.1016/j.ijpe.2014.11.014	FALSE	Missing AI relation and business model impact in core research.

Appendix 2: Search circles 1 and 2 with inclusion/exclusion criteria

Search Round	#	Name	Screening Result	Reason	Included Review	DOI/ISSN
1	1	Artificial intelligence in operations management and supply chain management: an exploratory case study.	Yes		No	10.1080/09537287.2021.1882690
1	2	Artificial intelligence in predicting the bankruptcy of non-financial corporations.	No	No research into business models; Only modelling of some economic actors; Wrong independent and dependent variable.	NA	10.24136/oc.2022.035
1	3	EXPLAINABLE AI IN CONSUMER BANKING.	No	Focus purely on artificial intelligence in businesses no relation to business models in the main research question.	NA	1531-0558
1	4	The impact of artificial intelligence along the insurance value chain and on the insurability of risks.	Yes	Impact of artificial intelligence on Insurance business models.	yes	10.1057/s41288-020-00201-7
1	5	Application of blockchain and smart contracts in autonomous vehicle	No	No mention of business models	NA	10.1016/j.tre.2022.102864

		supply chains: An experimental design.				
1	6	Predicting Credit Ratings using Deep Learning Models -- An Analysis of the Indian IT Industry.	No	Business model missing.	NA	10.14453/aabfj.v16i5.04
1	7	Assessing methodologies for intelligent bankruptcy prediction.	No	Only bankruptucy prediction with technical focus on prediction methods;	NA	
1	8	Think with me, or think for me? On the future role of artificial intelligence in marketing strategy formulation.	No	Focus on strategy formulation and artificial intelligence . Business model relation is not investigated.	NA	10.1108/TQM-12-2019-0303
1	9	Time series forecasting methods for the Baltic dry index.	No	Only forcasting of Baltic dry index, artificial intelligence missing;	NA	10.1002/for.2780
1	10	Extending business failure prediction models with textual website content using deep learning.	No	Business model missing; only research into most efficient method for artificial intelligence based business failure prediction	NA	10.1016/j.ejor.2022.06.060
1	11	A hybrid model for business process event and outcome prediction.	No	Business model missing; Forecast methodology research.	NA	http://dx.doi.org/10.1111/exsy.12079

1	12	Ensembles of Overfit and Overconfident Forecasts.	No	Business model missing.	NA	10.1287/mnsc.2015.2389
1	13	Financial time series analysis and forecasting with Hilbert–Huang transform feature generation and machine learning.	No	Business model missing; Purely methodological/technical paper.	NA	10.1002/asmb.2625
1	14	Expected Loan Loss Provisioning: An Empirical Model.	No	Business model missing; Purely methodological/technical paper.	NA	10.2308/TAR-2019-0128
1	15	Deep learning in business analytics and operations research: Models, applications and managerial implications.	No	Business model missing.	NA	10.1016/j.ejor.2019.09.018
1	16	A machine learning approach to univariate time series forecasting of quarterly earnings.	No	Business model missing; Predictive model development	NA	10.1007/s11156-020-00871-3
1	17	A Deep Learning-Based Decision Support System for Mobile Performance Marketing.	No	Business model missing; Predictive model development	NA	10.1142/s021962202250047x
1	18	Do Machine Learning and Business Analytics Approaches Answer	No	Artificial intelligence missing; Model for finding best business	NA	10.26650/ibr.2021.50.0117

		the Question of 'Will Your Kickstarter Project be Successful?		model for kickstarter platform.		
1	19	ECONOMIC TRENDS FORECASTING IN THE DEVELOPMENT OF HOTEL BUSINESS ENTERPRISES.	No	Artificial intelligence missing; business model missing;	NA	10.55643/fcaptp.5.46.2022.3876
1	20	Automobile insurance claim occurrence prediction model based on ensemble learning.	No	Business model missing.	NA	10.1002/asmb.2717
1	21	A framework for evaluating the business deployability of digital footprint based models for consumer credit.	No	Business model and artificial intelligence missing; Evaluation of deployability of UGDF models	NA	10.1016/j.jbusres.2022.07.057
1	22	Modelling land use/land cover changes prediction using multi-layer perceptron neural network (MLPNN): a case study in Makassar City, Indonesia.	No	Business model and artificial intelligence missing; predictive modeling;	NA	10.1080/00207233.2020.1804730
1	23	Predicting an ICT business process innovation as a digital transformation with machine learning techniques.	No	IV missing; Focus on modeling innovation	NA	10.1080/09537325.2022.2132927

1	24	Upper confidence bound integrated genetic algorithm-optimized long short-term memory network for click-through rate prediction.	No	Business model missing; modelling CTR	NA	10.1002/asmb.2671
1	25	Modeling Price Volatility Based on a Genetic Programming Approach.	No	Business model missing; mostly focussed on building a good model.	NA	10.1111/1467-8551.12359
1	26	Deep learning for energy markets.	No	Business model missing; Predictive model development;	NA	10.1002/asmb.2518
1	27	Self-supervised cross validation using data generation structure.	No	Business model and artificial intelligence missing; Methodological research into machine learning.	NA	10.1002/asmb.2701
1	28	Housing price prediction incorporating spatio-temporal dependency into machine learning algorithms.	No	Business model and artificial intelligence missing;	NA	10.1016/j.cities.2022.103941 Real estate
1	29	Adoption of blockchain + Internet of Things in demand forecasting of farm supply chain.	No	Main focus on technical side of prediction;	NA	10.1111/exsy.13187
1	30	A deep learning approach to real-time	No	Business model and artificial intelligence	NA	10.1016/j.trc.2019.08.010

		parking occupancy prediction in transportation networks incorporating multiple spatio-temporal data sources.		missing; methodological insights into machine learning.		
1	31	Electronic Retailing: Mapping the past for informing the future.	Yes	Systematic review of new technologies in retail	No	10.1080/09593969.2022.2152075
1	32	On the platform but will they buy? Predicting customers' purchase behavior using deep learning.	No	Only artificial intelligence model building	NA	10.1016/j.dss.2021.113622
1	33	Information security vulnerability prediction based on business process model using machine learning approach.	No	Prediction of business vulnerability information systems	NA	10.1016/j.cose.2021.102422
1	34	Hybridizing kernel-based fuzzy c-means with hierarchical selective neural network ensemble model for business failure prediction.	No	Only model building	NA	10.1002/for.2561
1	35	The Application of Micro-Modelling to Predicting Total Market Mix Potential.	No	Only artificial intelligence model building	NA	10.1080/0267257X.1988.9964047

1	36	Changing the game to compete: Innovations in the fashion retail industry from the disruptive business model.	Yes	Not only research on artificial intelligence on business model but is included	yes	10.1016/j.bushor.2020.01.004
1	37	Defective products management in a furniture production company: A data mining approach.	No	Business model missing; only model building	NA	10.1002/asmb.2685
1	38	Learning low-dimensional structure in house price indices.	No	Business model missing; Only model building	NA	10.1002/asmb.2653
1	39	Linear and Neural Dynamic Models: Shared Benefits Between the Industrial Customer and the ESCo From the Energy Services' Perspective.	Yes	Business model and artificial intelligence are there; but case study of specific technique;	No	10.1109/TSMCC.2006.875408
1	40	Managerial decision support system using an integrated model of AI and big data analytics.	No	Business model missing in abstract;	NA	10.1007/s10479-021-04359-8
1	41	Health care fraud classifiers in practice.	No	Business model missing; modelling focus	NA	10.1002/asmb.2633
1	42	Predicting shareholder litigation on insider trading from financial text: An interpretable	No	Business model missing; modelling focus	NA	10.1016/j.im.2020.103387

		deep learning approach.				
1	43	Identifying US business cycle regimes using dynamic factors and neural network models.	No	Business model missing; modelling focus	NA	10.1002/for.2658
1	44	A hybrid model for business process event and outcome prediction.	No	Duplikate article; business model missing; Forecast methodology research	NA	10.1111/exsy.12079
1	45	A BUSINESS MODEL IN AGRICULTURAL PRODUCTION IN SERBIA, DEVELOPING TOWARDS SUSTAINABILITY.	No	Model building;	NA	10.5937/ekoPolj1902437Z
1	46	Thriving in the digital age: The rise of the PAL supply chain and why businesses need a Copernican business revolution.	No	Artificial intelligence missing	NA	2516-1814
1	47	Deep learning for finance: deep portfolios.	No	Business model missing.	NA	10.1002/asmb.2209
1	48	Trademark-based framework to uncover business diversification	No	IV is missing;	NA	10.1016/j.compind.2020.103356

		opportunities: Application of deep link prediction and competitive intelligence analysis.				
1	49	Deep learning for spatio-temporal modeling: Dynamic traffic flows and high frequency trading.	No	Business model missing; only model building	NA	10.1002/asmb.2399
1	50	Design and Application of Handicraft Recommendation System Based on Improved Hybrid Algorithm.	No	Technical artificial intelligence investigation. Too little business relation.	NA	10.1142/S0218001422500082
1	51	Novelty detection based on learning entropy.	No	Purely technical on modelling with artificial intelligence	NA	10.1002/asmb.2456
1	52	Consistently accurate forecasts of temperature within buildings from sensor data using ridge and lasso regression.	No	Only artificial intelligence model building	NA	10.1016/j.future.2018.02.035
1	53	Big data driven Internet of Things for credit evaluation and early warning in finance.	No	Only artificial intelligence model building	NA	10.1016/j.future.2021.06.003

1	54	Using Machine Learning to Predict Corporate Fraud: Evidence Based on the GONE Framework	No	Only model building	NA	10.1007/s10551-022-05120-2	
1	55	Optimization of Tree Ensembles.	No	Only insignificant comments towards artificial intelligence business model relation.	NA	10.1287/opre.2019.1928	
1	56	ANALYTIC SURVEILLANCE: BIG DATA BUSINESS MODELS IN THE TIME OF PRIVACY AWARENESS.	No	No relation to artificial intelligence or business model	NA	10.3145/epi.2018.mar.19	
1	57	Business Failure Prediction of Construction Contractors Using a LSTM RNN with Accounting, Construction Market, and Macroeconomic Variables.	No	Model building.	NA	10.1061/(ASCE)ME.1943-5479.0000733	
1	58	Mixing mixed frequency and diffusion indices in good times and in bad: an assessment based on historical data	No	Model building.	NA	10.1007/s00181-022-02289-3	

		around the great recession of 2008.					
1	59	Radial basis neural tree model for improving waste recovery process in a paper industry.	No	Business model not in focus and artificial intelligence not given;	NA	10.1002/asmb.2473	
1	60	LOGIT BUSINESS FAILURE PREDICTION IN V4 COUNTRIES.	No	Model building.	NA	10.2478/emj-2019-0033	
1	61	Short-term LMP forecasting using an artificial neural network incorporating empirical mode decomposition.	No	Only artificial intelligence model building	NA	10.1002/etep.1949	
1	62	Credit Risk Analysis Using Machine and Deep Learning Models †.	No	Only artificial intelligence model building	NA	10.3390/risks6020038	
1	63	RETRACTED ARTICLE: Construction of business strategic planning structure model based on deep learning algorithm.	No	Retracted article	NA	10.1007/s10257-021-00502-x	
1	64	Decision tree based model of business failure prediction for Polish companies.	No	Model building.	NA	10.24136/oc.2019.022	

1	65	Risk assessment of failure of rock bolts in underground coal mines using support vector machines.	no	Model building.	NA	10.1002/asmb.2273	
1	66	A neural network ensemble approach for GDP forecasting.	No	Model building;	NA	10.1016/j.jedc.2021.104278	
1	67	A comparison of artificial neural network and multinomial logit models in predicting mergers.	No	Model building;	NA	10.1080/02664763.2012.750717	
1	68	ANN-based decision model for the reuse of vacant buildings in urban areas.	No	Only artificial intelligence model building	NA	10.3846/1648715X.2015.1101626	
1	69	Broad application of artificial intelligence for document classification, information extraction and predictive analytics in real estate.	No	Using artificial intelligence for document analysis and organisation in the real estate business; business model implications investigated. Extremely low quality journal;	NA	10.1177/0306307018823113	
1	70	Digital innovation the new paradigm for financial services industry.	No	IV and business model given; Focus on general digitalisation and business model ;Journal unknown in scorpus and	NA	1841-8678	

				other lists; only four weeks to publishing			
1	71	Predicting Recessions with Leading Indicators: Model Averaging and Selection over the Business Cycle.	No	Model building.	NA	10.1002/for.2345	
1	72	Predicting consumer gaze hits: A simulation model of visual attention to dynamic marketing stimuli.	No	Only artificial intelligence model building	NA	10.1016/j.jbusres.2019.03.034	
1	73	An investigation of the factors influencing cost system functionality using decision trees, support vector machines and logistic regression.	No	Model building; Unclear methodology; business model missing	NA	10.1108/IJAIM-04-2017-0052	
1	74	A novel approach to evaluating the business potential of intellectual properties: A machine learning-based predictive analysis of patent lifetime.	No	Only artificial intelligencemodel building	NA	10.1016/j.cie.2020.106544	
1	75	A data-driven method for future Internet	No	Only model building;	NA	10.1016/j.future.2018.12.054	

		route decision modeling.					
1	76	Non-parametric models with optimized training strategy for vehicles traffic flow prediction.	No	Only artificial intelligence model building	NA	10.1016/j.comnet.2020.107791	
1	77	A neural network based clustering procedure for bankruptcy prediction.	No	Only model building	NA	0743-2348	
1	78	The application of neural networks to predict abnormal stock returns using insider trading data.	No	No focus on changing business models only impact of artificial intelligence driven insider trading detection	NA	10.1002/asmb.466	
1	79	Entropy for Business Failure Prediction: An Improved Prediction Model for the Construction Industry.	No	Prediciton and model building oriented. Not implemented.	NA	10.1155/2013/459751	
1	80	Listen to me, my neighbors or my friend? Role of complementary modalities for predicting business popularity in location based social networks.	No	Concerned with some strategic considerations but mostly modeling and artificial intelligence is missing.	NA	10.1016/j.comcom.2019.01.004	
1	81	Dynamic customer churn prediction strategy for business	No	Only model building; business model missing	NA	10.1016/j.ipm.2021.102706	

		intelligence using text analytics with evolutionary optimization algorithms.					
1	82	Using Bayesian belief network and time-series model to conduct prescriptive and predictive analytics for computer industries.	No	Business model relation is not investigated.	NA	10.1016/j.cie.2017.12.003	
1	83	Predictive maintenance using tree-based classification techniques: A case of railway switches.	No	Only artificial intelligence model building	NA	10.1016/j.trc.2019.02.001	
1	84	MODELLING THE ADAPTATION OF BUSINESS CONTINUITY PLANNING BY BUSINESSES USING NEURAL NETWORKS.	No	Model building; no business model or artificial intelligence there.	NA	10.1002/isaf.326	
1	85	Unemployment Variation over the Business Cycles: a Comparison of Forecasting Models.	No	Model building; no business model or artificial intelligence there.	NA	10.1002/for.929	
1	86	Forecasting with Leading Economic	No	Model building; no business model or	NA	0007-666X	

		Indicators-A Neural Network Approach.		artificial intelligence there.			
1	87	Bankruptcy prediction by generalized additive models	No	Model building; no business model or artificial intelligence there.	NA	10.1002/asmb.658	
1	88	Estimation of default risk by stochastic modeling of the balance sheet: application to French industrial firms.	No	Model building; no business model or artificial intelligence there.	NA	0752-6180	
1	89	A combination selection algorithm on forecasting.	No	Model building; no business model or artificial intelligence there;	NA	10.1016/j.ejor.2013.08.045	
1	90	Model-supported business-to-business prospect prediction based on an iterative customer acquisition framework.	No	Only artificial intelligence model building.	NA	10.1016/j.indmarman.2013.03.006	
1	91	New approaches to origin and destination and no-show forecasting:Excavating the passenger name records treasure.	No	Only artificial intelligence model building.	NA	10.1057/palgrave.rpm.5170094	
1	92	A comparison of statistical methods for prenatal screening for Down syndrome.	No	Only model building;	NA	10.1002/(SICI)1526-4025(199904/06)15:2<89::AID-ASMB366>3.0.CO;2-K	

1	93	Fraudulent financial reporting detection and business failure prediction models: a comparison.	No	Model building	NA	10.1108/02686900810890625	
1	94	On business cycle fluctuations in USA macroeconomic time series.	No	Macro economic modelling	NA	10.1016/j.econmod.2015.11.022	
1	95	Predicting performances in business processes using deep neural networks.	No	Predictive application at the process level; business model missing.	NA	10.1016/j.dss.2019.113191	
1	96	Special Issue on Business and Industrial Statistics.	No	Model focus; no strategical application or relation investigated	NA	10.1002/asmb.481	
1	97	Customer relationship mining system for effective strategies formulation.	No	Business model missing.	NA	10.1108/IMDS-08-2013-0329	
1	98	A NONLINEAR EXTENSION OF THE NBER MODEL FOR SHORT-RUN FORECASTING OF BUSINESS CYCLES.	No	Macro economic modelling	NA	10.1111/j.1813-6982.2005.00029.x	
1	99	Detecting corporate misconduct through random forest in China's construction industry.	No	Model building and no direct artificial intelligence and business model ;	NA	10.1016/j.jclepro.2020.122266	

1	100	The Application of Neural Networks and a Qualitative Response Model to the Auditor's Going Concern Uncertainty Decision.	No	Only artificial intelligence model building	NA	10.1111/j.1540-5915.1995.tb01426.x	
1	101	A Network Based Economy Model Using the Concept of Diversity, Independence and Decentralization (D-I-D).	No	Quality questionable; Topics too high level;	NA	0975-7848	
1	102	Asymmetries in Macroeconomic Time Series in Eleven Asian Economies.	No	Macro economic modelling	NA	1543-1614	
1	103	Guidelines for assessing the value of a predictive algorithm: a case study.	No	Too high level and focussing on the pure value creation aspect of predictive modelling. No link to overall business model concept.	NA	10.1057/s41270-017-0027-1	
1	104	Value-capture in digital servitization.	Yes	Fitting independent variable (Artificial intelligence) and business model .	yes	10.1108/JMTM-05-2021-0168	
1	105	Proactive customer retention management in a non-contractual B2B setting based on	No	Business model missing.	NA	10.1016/j.indmarman.2022.09.023	

		churn prediction with random forests.					
2	1	The Application of Micro-Modelling to Predicting Total Market Mix Potential.	No	Sales forecasting model; missing business model and artificial intelligence;	NA	10.1080/0267257X.1988.9964047	
2	2	Generating Explanations for Goal-Based Decision Making.	No	Model building and application only in political setting;	NA	10.1111/j.1540-5915.1992.tb00458.x	
2	3	On the usage of qualitative reasoning as an approach towards enterprise modelling.	No	Model building; business model missing;	NA	10.1007/BF02031718	
2	4	AI models for business process reengineering.	No	Low quality abstract; Typos etc; Reengeneering as topic not business model;	NA	1094-7167	
2	5	Inductive Model Analysis Systems: Enhancing Model Analysis in Decision Support Systems.	No	Focussed on the model application not the implication for businessmodels.	NA	10.1287/isre.7.3.328	
2	6	Business Process Modeling from the Control Perspective: The AI Planning Approach.	No	Management control implications of applying artificial intelligence.	NA	10.1002/(SICI)1099-1174(199706)6:2<121::AID-ISAF121>3.0.CO;2-B	
2	7	Classification based on rules and thyroids dysfunctions.	No	Medical paper; no implications for artificial intelligence or business model .	NA	10.1002/(SICI)1526-4025(199910/12)15:4<319::AID-ASMB396>3.0.CO;2-H	

2	8	Integrating Machine Learning and Workflow Management to Support Acquisition and Adaptation of Workflow Models.	No	About improving processes and workflows in company using artificial intelligence but not about actually using artificial intelligence and business model .	NA	10.1002/1099-1174(200006)9:2<67::AID-ISAF186>3.0.CO;2-7	
2	9	Development of a Case-Based Decision Support System for Process Modeling in BPR.	No	Business process modeling; No business model or artificial intelligence.	NA	10.1002/1099-1174(200006)9:2<93::AID-ISAF181>3.0.CO;2-H	
2	10	Knowledge management with a human face.	No	Very general article but potentially relevant ideas. Last publication of journal in 2004; Thus too old;	NA	10.1075/cat.8.2.05enn	
2	11	New approaches to origin and destination and no-show forecasting:Excavating the passenger name records treasure.	No	Modeling of passenger no shows; No link to business model .	NA	10.1057/palgrave.rpm.5170094	
2	12	Automatic Classification of Heartbeats Using ECG Morphology and Heartbeat Interval Features.	No	Modeling Heartbeats; No business relation.	NA	10.1109/TBME.2004.827359	
2	13	Strategic planning for value-based	No	Only artificial intelligence model building	NA	10.1108/00251740410555434	

		management: An empirical examination.					
2	14	Assessing the of potential of e-business models: towards a framework for assisting decision-makers.	No	Artificial intelligence is not investigated.	NA	10.1016/j.ejor.2003.07.013	
2	15	Editorial.	No	Only editorial.	NA	10.1002/asmb.543	
2	16	A tutorial on ν-support vector machines.	No	Practical implications for businesses of machine learning; No business model;	NA	10.1002/asmb.537	
2	17	Ridge directional singular points for fingerprint recognition and matching.	No	Modeling of non relevant topic (Fingerprints)	NA	10.1002/asmb.611	
2	18	Balancing performance measures for information security management.	No	Artificial intelligence is missing in the research topic.	NA	10.1108/02635570610649880	
2	19	Linear and Neural Dynamic Models: Shared Benefits Between the Industrial Customer and the ESCo From the Energy Services' Perspective.	Yes	Indepth case study in utility for artificial intelligence application and business model; Very old paper and modelling is in focus.	No	10.1109/TSMCC.2006.875408	
2	20	Intelligent decision system and its application in business	No	Focus on a specific artificial intelligence based decision tool; Focus on general	NA	10.1016/j.dss.2005.03.004	

		innovation self assessment		innovativeness and scoring the business not on the businessmodel.			
2	21	Time-Limited Leases in Radio Systems.	No	Artificial intelligence is missing in the research topic.	NA	10.1109/MCOM.2007.374422	
2	22	Towards a web services and intelligent agents-based negotiation system for B2B eCommerce	No	Focus on artificial intelligence tool to help with negotiations in the B2b E-commerce space; No direct insights.	NA	10.1016/j.elerap.2006.06.007	
2	23	A knowledge hierarchy model for adaptive multi-agent systems.	No	Tool to improve software adaptibility; business model and artificial intelligence missing;	NA	10.1504/IJCAT.2008.017715	
2	24	Semantics and analysis of business process models in BPMN	No	No relation of artificial intelligence tool to business model ;	NA	10.1016/j.infsof.2008.02.006	
2	25	STRATEGIC CONTROL AND THE PERFORMANCE MEASUREMENT SYSTEMS.	No	Focus in management control systems and business model but no artificial intelligence .	NA	1222-569X	
2	26	Panel 2: The Implications of Digital Scholarship for Research Libraries: Challenges of Access and Preservation.	No	Artificial intelligence missing;	NA	10.1080/01930820902785124	
2	27	Weaving a semantic grid for	No	Artificial intelligence missing;	NA	10.1080/00207540701769966	

		multidisciplinary collaborative design.					
2	28	BUILDING CUSTOMER MODELS FROM BUSINESS DATA:: AN AUTOMATIC APPROACH BASED ON FUZZY CLUSTERING AND MACHINE LEARNING.	No	Model building no relation to Business models.	NA	10.1142/S1469026809002692	
2	29	Developing a unified framework of the business model concept.	Yes	Business model concept in information systems. Focus on linkages between the information systems and business model . No artificial intelligence.	No	10.1057/ejis.2010.21	
2	30	Team and Group Development the AI Way.	No	Artificial intelligence as standin for a non known type of organisation.	NA	1741-8224	
2	31	A Network Based Economy Model Using the Concept of Diversity, Independence and Decentralization (D-I-D).	No	Macro economic modelling	NA	0975-7848	

2	32	Appreciative Leadership for Sustainable Development in India.	No	Artificial intelligenceas standin for a non known type of organisation; Note: Excluding any further articles from this journal from the search approach;	NA	1741-8224	
2	33	Normative agent-based simulation for supply chain planning.	No	Modelling of supply chain; not related to core operating model; Link to business model missing;	NA	10.1057/jors.2010.144	
2	34	A reference framework following a proactive approach for Product Lifecycle Management	No	Modelling of Product lifecycle no relation to business model ;	NA	10.1016/j.compind.2011.04.004	
2	35	Single-machine scheduling with general sum-of-processing-time-based and position-based learning effects	No	Business model is missing; Mostly modelling.	NA	10.1016/j.omega.2010.10.002	
2	36	THE CONCEPT OF THE IMPLEMENTATION OF INVENTOMRY MANAGEMENT BY THE SUPPLIER WITH THE USE OF AGENT TECHNOLOGY.	No	Logistics industry, no focus on business model but only on improvement of efficiency using a agent based model.	NA	1895-2038	

2	37	BUSINESS CYCLE DRIVERS IN LITHUANIA.	No	Macro economic modelling	NA	1392-2637	
2	38	Enterprise transformation: An analytics-based approach to strategic planning.	No	Focus on the business planning method and descriptive and diagnostic analystics; No artificial intelligence .	NA	10.1147/JRD.2012.2217673	
2	39	Entropy for Business Failure Prediction: An Improved Prediction Model for the Construction Industry.	No	Already Research approach 1a.	NA		
2	40	A comparative analysis of machine learning systems for measuring the impact of knowledge management practices	No	artificial intelligence for knowledge management given; missing relation to Business models;	NA	10.1016/j.dss.2012.10.040	
2	41	THE USE OF BPMN FOR MODELLING THE MES LEVEL IN INFORMATION AND CONTROL SYSTEMS.	No	Business process modeling; No business model or artificial intelligence	NA	10.12776/QIP.V17I1.68	
2	42	Small Steps that Matter: Incremental Learning, Slack Resources and Organizational Performance.	No	Artificial intelligence missing;	NA	10.1111/j.1467-8551.2011.00793.x	

2	43	A framework for the identification of reusable processes	No	Research about alignment of information systems and business goals;	NA	10.1080/17517575.2013.805247	
2	44	An integrated supply chain model with errors in quality inspection and learning in production.	No	No relation to business model ; Focus on supply chain optimization;	NA	10.1016/j.omega.2013.02.002	
2	45	WoMan: Logic-Based Workflow Learning and Management.	No	Model for workflow optimization, no relation to business models.	NA	10.1109/TSMC.2013.2273310	
2	46	Mining User Knowledge for Investigating the Facebook Business Model: The Case of Taiwan Users.	No	Only artificial intelligence model building	NA	10.1080/08839514.2014.927695	
2	47	Supporting Process Model Validation through Natural Language Generation.	No	Business process modelling: Missing business model .	NA	10.1109/TSE.2014.2327044	
2	48	APPRECIATIVE INQUIRY AS A MODEL FOR ASSESSING THE VALUE OF BUSINESS SCHOOL EDUCATION.	No	Research into efficacy of business school education;	NA	1948-6413	
2	49	Statistical learning for variable annuity	No	Only artificial intelligence model building	NA	10.1002/asmb.2009	

		policyholder withdrawal behavior.					

……. Appendix continues and is available under:

Appendix Link