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Reflections on AI and Business Models.

The Good, the Bad and the Ugly

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Abstract

Over the last five years, several scholars from a range of disciplines have started to analyse how Artificial Intelligence (AI) affects businesses outcomes. This research effort has produced many predictions on the expected impact of automation on labour demand and equilibrium employment. However, most of the expected results are dependent on how businesses change their behaviour due to adopting AI. We argue that, as AI diffuses across the economy, changing behaviour is a necessary outcome for incumbents: the argument is that the diffusion of AI across an industry generates the conditions for a process of value migration from incumbents to new entrants (Helper et al., 2018); in these cases, the only mechanism available to incumbents to offset the negative impact of the migration process is by changing the architecture of their business, i.e. the business model. However, companies can choose from several AI-driven business models; their preference for one model is driven by many industry-level factors such as technical standards, the structure of the technology industry and the presence of an ethical framework for the use of AI. The current paper summarises the existing literature on business model innovation and AI; it then analyses the industry-level factors that may shape the business-level preference for specific business models. Finally, the paper offers some suggestions for future research in the area.

1. Introduction

Interest in Artificial Intelligence (AI henceforth) has grown over the last five years. This interest has been spurred by many factors, including the availability of high volumes of data (both structured and unstructured), the dramatic fall of the costs of storing and processing large volumes of data, and cloud computing and platforms' availability. Unsurprisingly, several governments have started to invest substantial amounts of public funds into large AI research programmes[1]. What is AI exactly? In a nutshell, AI tries to simulate human intelligence through computer systems: more specifically, intelligent systems try to mimic the capability of humans to learn (or acquire new information), reason and self-correct (Calo, 2017). Importantly AI as a term covers a large variety of technologies ranging from machines that can recognise objects and make predictions to systems that have a sense of consciousness and can process their current state.

In economic terms, AI is modelled as a General Purpose Technology (GPT) that can improve productivity once deployed at scale (Brynjolfsson et al., 2017). Most of our understanding of how AI can affect economic outcomes is very much shaped by discussions on job losses and its impact on equilibrium employment (Acemoglu and Restrepo, 2019; Aghion et al., 2019). Recently, researchers from several disciplines have tried to broaden the discussion by focusing on the impact that AI may have on organisations by changing their internal processes, core capabilities and eventually their business models (van Der Meulen, 2018; Agrawal et al., 2019). According to some authors, AI's impact on business outcomes may be rather sizable (see, for instance, Brynjolfsson and McAfee, 2014). In reality, given the emerging nature of the technology, it is not easy to quantify these impacts and the mechanisms through which AI will affect their performance (Brynjolfsson et al., 2017). At the moment, the primary thinking is that AI may affect business performance by allowing businesses to use resources more efficiently over time. This outcome is mostly achieved by having AI systems to perform routine tasks which can be learned by software agents ('bots'), which can then prioritise tasks, manage routine interactions with other teams (or other bots), and plan schedules (Acemoglu and Restrepo, 2019; Aghion et al., 2019). AI can also help businesses to streamline their activities and enrich their offerings with new and "smart" products[2] and lead to the adoption of new business models like Uber and Airbnb[3]. Eventually, increases in efficiency and improved products may translate into increases in productivity and profits. There are already examples of organisations that use AI to either minimise costs or launch new products: for instance, Amazon already uses AI to plan the most efficient routes for delivery while legal firms tend to use AI to search through documents and legal records[4].

Most of the benefits that AI can generate to businesses (and eventually translating into macroeconomic performance) are contingent on changes that businesses make to their business models. Unsurprisingly, understanding how AI shapes new business models is key to understanding how it can influence future economic outcomes well beyond the existing narrative around job losses and technological unemployment (Arntz et al., 2016; Acemoglu and Autor, 2011; Bessen, 2018; OECD, 2015). For this, it is worth starting from a business model definition. Business models are usually defined as the "design or architecture of the value creation, delivery and capture mechanisms" of a business (Teece, 2010). A business model is about the benefits business creates, how it organises itself to do so, and how it will capture value. Business models *per se* are not immutable but tend to change as the business environment changes (Chesbrough, 2002, 2007, 2010, 2013; Lindgardt et al., 2009). In turn, this leads to the notion of business model innovation which is not about a new range of products or services offered by organisations, but it is a fundamental change of one of the elements of the current business model (Zott and Amit, 2010; Amit and Zott, 2015). This change can be in either the value proposition or the revenue model. In each case, the change has to provide the business with a new value source that can be used to sustain competitive advantage (Zott and Amit, 2010).

A typical driver of business model innovation is the emergence of a new technology that creates value migration conditions within industries (Teece, 2010; Zott and Amit, 2010; Foss and Saebi, 2017). In some cases, changing the architecture of their business (i.e. the business model) can be the only mechanism available to incumbents to offset the new technology's negative impact on their performance (Zott and Amit, 2010). A new business model can help incumbents cope with the changing technological landscape and ensure that the new technology's emergence does not compromise business outcomes. This fact applies to AI as well. In this case, businesses can choose from several new business models where AI is used to create and capture value, implying that AI's adoption does not necessarily translate into net job losses.

Despite the relevance of the topic, not much is known about the relationship between business model innovation and AI. There is a small literature on business model innovation and AI that struggles to disentangle the interdependencies between technology development and business model innovation (Tongur and Engwall, 2014; Wage and Crawford, 2017; Antonescu, 2018). In other words, AI developments are assumed to "be" the business model innovation even if in reality, the two concepts are separated. The underlying issue here is that while there is a good understanding of how AI (as new and emerging technology) powers new businesses, it is more difficult to understand how the choice of a new business model is intertwined with technology development and how industry-level factors can explain the choice of specific business models. As a result, there are essential questions in this field whose answers are unclear: how do businesses choose new business models? What are the factors shaping their choices? However, it will not be possible to answer these questions until we have a deeper understanding of how AI drives business model innovation.

Against this background, this paper summarises the literature on AI and business model innovation by highlighting the mechanisms that link the two key variables. Our fundamental hypothesis is that the deployment of AI across an industry creates new mechanisms for value creation in the industry; this may result in new firms generating value in an industry as incumbent firms may no longer be competitive as in the past. This is the so-called **"value migration"** phenomenon, and in these cases, changes to the incumbents' business models are needed to generate value once more. We argue that incumbents have to change the business models once AI is adopted, but at the same time, the decision of what is changed (i.e. which component of the business model is changed) is up to the business. It is contingent on a mix of industry-level factors that can influence businesses' capability to identify successful new business models. In other words, adopting AI does not exclusively imply that businesses generate profits through cost reduction, as suggested by much of the economics literature.

Our analysis will start from the concept of value migration and how AI's deployment in an industry implies that the mechanism for value generation moves somewhere else in the industry; in this case, business model innovation is the only mechanism for businesses to try to generate value. We plan to discuss how AI systems are reshaping business models' mechanisms, approaches and founding elements (such as organisation, infrastructures, customers or value propositions). We will then move to map the business model innovations we can identify from the literature and produce a taxonomy of emerging AI-driven business models that will help understand how businesses decide to incorporate AI into their activities. Once we have laid out the different models that businesses can adopt when AI is deployed at scale in an industry, the analysis will focus on the industry-level factors that shape a specific business model's choice once an emerging technology is deployed. Our analysis will focus on many factors, including the role of technology standards, the technology industry's characteristics, and the ethical framework within which businesses operate. While the list is not exhaustive, we have chosen the list of important factors at this point given the nature of AI as an emerging technology.

The paper wants to offer a summary of the existing literature in this area. It does not want to present new results but instead plans to highlight existing literature gaps, hoping these may spur new research in the topic. It is essential to highlight that lack of data on AI hampers empirical research in this area (Raj and Seamans, 2017); therefore, in our work, we will mostly refer to qualitative studies and grey literature that underpins most research in the field. In this respect, this work's vital purpose is to identify where formal research is needed to help us understand how business models change as AI diffusion across economies accelerates.

The structure of the paper as follows. Section 2 will provide a brief introduction to AI and its different varieties. Section 3 will then focus on value migration in industry and business models. Therefore, it will first define value migration and what it implies for existing business models. The discussion is conducted in the context of the AI and the implications of its diffusion for the whole industry. Section 4 provides a taxonomy of the new business models that have emerged due to AI and discusses these new business models' main features. Section 5 will then analyse the key factors that drive the emergence of new business models. Importantly, we will analyse a set of industry-level factors that may condition the new business model's choice. We will also discuss the role of an ethical framework on the emergence of the different business models. Finally, Section 6 offers some concluding remarks and some reflections on existing gaps in our knowledge of business models that can inform future research in the field.

2. What is AI?

2.1 Defining AI

"Artificial Intelligence" is a generic term to indicate the capability of computing systems to mimic human intelligence (Bughin et al., 2017a, 2017b; Urwin, 2017, Boden, 2016)[5]. The history of AI is well known: in 1956, McCarthy organised a research group focusing on developing systems that can reproduce human intelligence (McCarthy, 2006; McCorduck, 2009). While the original research programme in AI revolved around the development of generalised AI (i.e. codes that could reproduce the human intelligence in the broadest sense), the current AI research wave focuses on narrow AI, i.e. AI that mimics some critical features of human intelligence such as the capability to recognise patterns and linguistic symbols. Currently, AI can detect data patterns and extract information from images, written language and speech (Saon et al., 2017; Taigman et al.,

2014) although the pattern detection has to meet human-defined criteria. Nowadays, the improvement of computational power has created the conditions to create several applications of AI across several industries. These applications mostly focus on automation of routine tasks, image and voice recognition or translating languages (Liu et al., 2017; Marcus, 2018) with machine learning being the primary technology underlying these applications of AI (Dean, 2014; Manyka et al., 2017; Bughin et al., 2017).

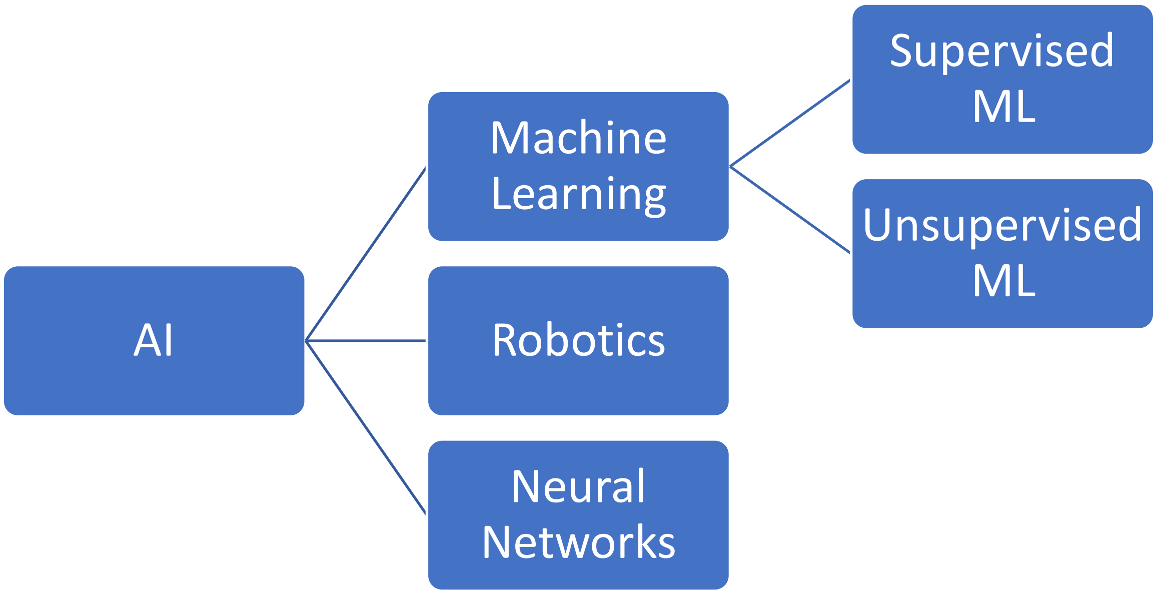

Figure 1. Different types of AI

Technically, machine learning involves using algorithms to improve a computer's learning performance on a specific task by relying on patterns generated from sample data (Boden, 2016). Machine learning is of different types. The first type is called unsupervised learning and, in this case, algorithms have to find a structure in the data using unlabelled data. Clustering is classified as a type of unsupervised machine learning; its primary goal is to find natural groups or clusters within data. Clustering is commonly used in marketing to segment customers according to income or other factors.

The second type of machine learning is called supervised learning, and it involves using a labelled data set[6] to train a model, which can then be used to classify or sort a new, unseen set of data. Predictive coding software is an example of supervised learning. In this case, the training session "teaches" the algorithm what to look for in documents or data and then can rank them. It is very commonly used within legal practices as this type of technique allows to rank documents based on their importance.

Finally, the third type of machine learning is called reinforcement learning and uses rewards to enforce learning. The assumption here is that agents in an environment will learn to maximise their rewards (Garnelo et al., 2019). DeepMind's AlphaGo uses reinforcement learning; equally, robotics tends to rely on reinforcement learning for this purpose.

Deep learning (Serafini et al., 2019) and deep neural networks have received much attention recently (see Burghin et al., 2017; Marcus, 2018; AlphaGo Deepmind, 2019; Besold et al., 2019); neural networks are aggregates of machine learning algorithms that work together to solve more complex problems and mimic the behaviour of neurons in a human brain (Schalkoff, 1997; Garcez et al., 2008, 2015; Urwin, 2017). Deep neural networks have many layers, which allows them to solve more complicated problems (Marcus, 2018). Deep neural networks are used for speech/image recognition, fraud detection, providing recommendations and natural language processing (Chiu et al., 2018). Deep neural networks have received many applications in real life. It is behind the Alpha 2 robot from UbiTech and driverless cars developed by Pony.ai. Deep neural networks are also used for systems of automatic face recognition that use real-time cameras.

All businesses face choices about where to use AI and where it might make the most impact. Experts predict multiple areas of impact for AI in health care, including improving radiology diagnoses, making devices smart, and identifying new infection patterns (Garbuio and Lin, 2019). Consumer packaged goods (CPG) companies can generate more than 10% of their revenue growth through AI that would allow them to do more predictive demand forecasting, more relevant local assortments, personalised consumer services and experiences, optimised marketing and promotion ROI, and faster innovation cycles. Facial recognition, biometric verification, voice recognition, and eye retina verification are examples of techniques that rely on AI technologies. Equally, AI supports regulatory compliance in several industries. For instance, AI allows businesses to be compliant with anti-money-laundering regulations. Equally, employee verification and customer identity verification software are used by business to reduce the risk of fraud. Finally, AI is used to manage data and reduce the risk of data theft or forgery.

2.2 AI-as-a-platform

While differences among the many AI types are clear, how AI systems get embedded in existing IT systems is less clear (Boston Consulting Group, 2019). Typical IT systems consist (in a very simplistic way) of data input, software to process the input and some interface so that users can get access to the output (Boston Consulting Group, 2019). However, some AI systems may be more complicated than that as they need to have access to training data, which is now a key component (Varian, 2019). Some AI systems also build upon other (underpinning) AI-based tools; some AI systems can also offer AI integration services that put together algorithms to solve specific problems. AI services can be combined and may include general applications (like natural language processing and image recognition which cannot be used on their own) and applications that are specific to a problem[7]. Some of these services rely on machine learning, making it possible for the AI systems to select algorithms for a specific problem. Finally, in AI systems, the user's capability to interpret and assess the quality of the output is paramount because user interface (and its interpretability) is a much more important component than in traditional IT systems. As a result, the architecture of the new IT system (cum AI) can be rather complicated.

A simple example put forward by Varian (2019) can help clarify the point. Suppose a business wants to deploy a new system based on machine learning in a specific area. The organisation needs to build the so-called "data pipeline" that is the data infrastructure that collects the data that will be analysed through the machine learning algorithms. The data pipeline often combines data from different sources (i.e. both internal and external to the business) and of different types (that is, both structured and unstructured data) in a "data lake" that will be then used for the analysis. Importantly these are different from the data that is required to train the algorithm. Building up the data pipeline and assembling the training data can be the most expensive part of building AI systems and mostly because data may be stored in different systems and formats and the volume of the data is such that traditional storage methods may not be that useful.

Once the data have been organised, they need to be stored in a data warehouse, giving the analytics team access to the data for the analysis and visualisation. The volume of data required for AI projects is often more cost-effective for companies to use large tech companies' cloud computing facilities than investing in a new data warehouse. Unsurprisingly, AI has started to be integrated into existing platforms by the major platform providers (so-called AI as-a-service)[8]. In these cases, AI is a component of the platform, mostly hidden in the background. Also, platform providers can offer optimised software to specific organisational problems using the most common algorithms. Notably, cloud providers offer AI services (examples include speech and image recognition) which have already been trained by the platform provider[9]. Indeed, chatbots and digital assistants are the first examples of AI-as-a-service as voice recognition, and natural language processing is critical to users. As AI becomes one of the platforms' services, businesses do not need to build their own AI systems or build up extensive training data. In other words, the mechanisms for the deployment of the AI have evolved so that users can easily have access to advanced AI without the need to invest in the development of internal AI capabilities.

3. Impact of AI on businesses: What do we know so far?

3.1 AI as a General Purpose Technology. The literature that studies AI's impact on businesses and economic outcomes more generally starts by arguing that AI (namely machine learning, robotics and associated technologies) is an example of a General Purpose Technology (or GPT). The concept goes back to Bresnahan and Trajtenberg (1996) who defined GPT as a pervasive technology, attracting complementary innovations and susceptible to further improvements. They provided many examples of GPTs that have significantly impacted economies such as the steam engine, electricity and computers (Brynjolfsson and Hitt, 2000; David and Wright, 2006). GPTs tend to increase the productivity of businesses across most industries and spur several complementary innovations that enhance the positive effect of the GPTs on productivity by creating new supply chains or allowing businesses to exploit economies of scale (Jovanovic and Rousseau, 2005; Cockburn et al., 2017).

AI (and in particular machine learning as the underlying methodology) appears to fit the description provided by Bresnahan and Trajtenberg (1996). Agrawal, Gans, and Goldfarb (2017, 2018) pointed out that machine learning, in general, is particularly suited for automating tasks where prediction matters and they can be applied to most tasks currently performed by humans. Besides, AI systems embedded with machine learning can learn and improve over time (Brynjolfsson et al., 2018).

Interestingly, the improvement process can be led by an algorithm itself rather than by a software engineer. For instance, machine learning codes can identify the best functions linking inputs and outputs and can do so even without supervision (Brynjolfsson and McAfee, 2017; Mitchell and Brynjolfsson, 2017). Also, machines can share knowledge and learn from each other: once a machine acquires skill in one location, it can be replicated across digital networks thanks to cloud computing availability [10]. Finally, machine learning systems can spur a variety of complementary innovations. Indeed, machine learning can help engineers develop a broader set of additional applications that can enhance existing machine learning algorithms' capabilities.

3.2 The impact of AI on businesses and economic outcomes in general. Most of the economic analysis on AI has focused on the impact that robotics (or automation in general) may have on existing jobs and through this route on economic growth (Furman and Orszag, 2015; Furman, 2017; Solomonoff, 1985). The key papers here are those by Zeira (1998), Acemoglu and Autor (2011) and Acemoglu and Restrepo (2016) - discussing the impact of automation on tasks, productivity - and work and by Aghion et al. (2019) - focusing on economic growth and automation. Automation is assumed to be exogenous, and the incentives for introducing AI are related to cost reduction.

3.3 Automation and Labour Market.

In the model proposed by Acemoglu and Restrepo (2016), automation will displace workers in tasks. Interestingly, it is not only routine tasks that are replaced in this model but also tasks that require high skills. As a result, labour demand will decrease (despite the increasing productivity of labour), and employment in equilibrium will be much lower, everything else being equal. There are some c at work in the model: the increase in productivity of the existing workforce will expand the economy, which will increase the demand for jobs whose tasks cannot be automated. Additionally, increasing automation triggers an increase in capital investment which will generate labour demand in industries like robotics and engineering. Finally, automation will generate new jobs which will support robots and their maintenance (for instance). Importantly, even if there are factors that may slow down the displacement effect of AI on labour, it is essential to bear in mind that the adjustment will be costly as workers will be searching for new jobs and will need to retrain. However, the speed of adjustment is endogenous as it will be determined by firm-level decisions about the adoption of AI and by workers about education and training.

3.4 What is the impact of automation on economic growth? Aghion et al. (2019) have studied the issue, and they point out that the positive impact of automation on growth may be constrained by the fact that sectors with relatively slow productivity growth may experience increases in their size. This phenomenon has been compared to Baumol's "cost disease" (Baumol, 1967) which refers to the fact that sectors with slow productivity growth may increase in size even if they do not grow faster than the other industries that experience fast productivity growth. When Baumol's observation is applied to models where fast productivity growth is triggered by automation, sectors with slow productivity growth slow down economic growth. As a result, the labour share remains substantial even if the extent of automation is pervasive.

There are no models that focus on other types of AI (machine learning is the key example here) and their impact on the activities of the businesses. In reality, most of the understanding of the impact of AI on economic outcomes is driven by the analysis of automation and its impact on productivity growth and through that route on economic growth. While these results are perfectly reasonable in the context of what we expect the impact of automation on economic outcomes to be, they do not account for the fact that AI is not only automation and that businesses use AI in ways that are well beyond the cost-saving paradigm that underpins most of the research on the economic impact of AI. Indeed, businesses may use AI to improve consumer experience or deliver services that are closer to what the consumers want (Rayna, 2008; Rayna and Striukova, 2009). The impact of these alternative uses of AI on productivity and ultimately economic growth is not well understood; however, to be able to do so, it is crucial to understand how AI shapes business models and how incumbents continue to create value with AI. In other words, the focus on the analysis has to move to business models even if the concept itself does not have any grounding in economic theory (that mostly focuses on pricing and value capture). Still, studying business models makes sense in economic models where innovation can be disruptive and therefore, incumbents will have to identify new mechanisms to survive by developing new value propositions (Gambardella and McGahan, 2010).

- **Value Migration and Business Models**

In the previous section, we have summarised the existing literature on the potential impact of AI on economic growth and economic performance. As suggested previously, a full assessment of AI's impact on economic outcomes requires an understanding of how organisations embed AI into their business model.

New entrants adopt radically different business models that rely on innovative uses of AI, and therefore the mechanisms used by incumbents to create value may no longer be fit for purpose. There are many examples of this: Uber and Airbnb are well-known entrants that use a different business model than incumbents thanks to AI and eventually, end up dominating their respective industry segments. How can incumbents react? Several authors have pointed out that business model innovation is the primary mechanism that incumbents can use to offset value migration's negative implications (Lindgardt et al., 2009; Gassman et al., 2017). Our main claim here in the context of AI-driven value migration is that business model innovation is not limited to introducing new products or new processes (Sorescu, 2017). However, it requires a complete re-thinking of the mechanisms that connect the different components of the existing business model:

the mechanisms by which value is created and captured. Therefore, the purpose of this section is to identify different patterns of business model innovation which enable businesses (and organisations in general) to rebuild their business logic.

We will first define the concept of the business model and its components; we will then introduce the concept of industry-level value migration. Finally, we will provide a framework to analyse business model innovation and taxonomy that summarises the main types of business model innovation we can observe in real life.

4.1 Defining Business Models

Every organisation has a business model that describes how value is created, delivered and finally captured by the organisation. A business model addresses the critical question: "how does one build a competitive advantage and generate a profit?" Business models can be considered a concise representation of an organisation's internal thinking of creating value for its stakeholders (Magretta, 2002; Shafer et al., 2005; Sorescu et al., 2011; Teece, 2010). Business models allow firms to identify the connections between choices and performance and ensure that internal decisions are consistent among each other (Shafer et al., 2005). These can be related to the value chain structure (Zott and Amit, 2010) or the value proposition offered to customers (Morris et al., 2005; Teece, 2010).

Driving factors behind the interest in business models include the growth of the Internet (as an alternative distribution channel) and e-commerce, outsourcing and offshoring of many business activities and more generally the fact that value capture mechanisms are different from the value capture mechanisms used in manufacturing industries which mostly relied on the scale (Wirtz et al., 2010; Wirtz et al., 2016). Still, there is no consensus on what is a business model (Foss and Saebi, 2017, Zott et al., 2011) although both practitioners and academics agree that a good business model has to generate value while enabling value capture (Teece, 2010; Foss and Saebi, 2017).

Let us go through some definitions:

- A traditionally used definition of a business model is provided by Teece (2010) and Zott and Amit (2008). According to them, **a business model represents how an organisation creates, delivers and captures value in conjunction with other partners.** In their view, without a well-developed business model, businesses will fail to capture value from their activities. Indeed, developing a successful business model is insufficient to assure competitive advantage as an imitation of business models is often straightforward. A business model can create a competitive advantage if it is hard to replicate.

- Other definitions suggest that the business model is "*a theoretically anchored robust construct for strategic analysis*" (Zott and Amit, 2013). Christensen et al. (2016) define business models as *complex systems or configurations of highly interdependent elements* (Christensen et al., 2016; Zott and Amit, 2007). Massa et al. (2017) summarised three distinct interpretations of a business model: a) *business model summarises the logic with which an organisation achieves its goals*; b) business model summarises *how a business perceives the relationships among its different functions*, and c) business models are *simplified descriptions of how an organisation functions*[11].

Most papers on business models emphasise that business models are made of different components that may explain how businesses do business (Amit and Zott, 2001; Osterwalder et al., 2005; Osterwalder and Pigneur, 2010; Morris et al., 2005). Again, there are several descriptions of these components. Some authors identify four elements:

- A customer value proposition,
- A profit formula,
- Key resources and
- Key processes that allow consistently delivering the value proposition.

The literature suggests that the same business can use multiple business models, and they differ along with different distribution costs, arrangements to source inputs and satisfying customer needs.

4.2 Value Migration and Business Model Innovation

Initial work on business models had assumed a static relationship among the many elements that made up a business model and did not consider the impact of the environment on such relationships (Osterwalder and Pigneur, 2010; Teece, 2010; Massa et al., 2017). At the same time, organisational-level decision making is acknowledged to be influenced by the business environment and its changes. Therefore business models cannot be immune from this process as in real life, business models change continuously because of technological innovation, changing regulation, changing industrial structure and so on (e.g., Afuah and Tucci, 2001). As pointed out by several authors (Chesbrough, 2010; Sanchez and Ricart, 2010; Zott et al., 20baden11; Massa et al., 2017), to understand how changes in the environment alter the relationship among the different business model elements, it is essential to adopt a different perspective that focuses on the drivers of business model innovation.

Research on business model innovation has tried to articulate the relationship between industry-wide phenomena (like the emergence of new technology) and business models and how the resulting strategic choices available to firms unfold (Koen et al., 2011). Therefore, literature has developed the concept of **value migration** (Jacobides and MacDuffie, 2013; Slywotzky, 1996) that is the change of the sources that create profits (Jacobides and MacDuffie, 2013; Slywotzky, 1996). From the consumers' standpoint, the value can migrate from established incumbents to new entrants with better products (Slywotzky, 1996). While some firms absorb value from other firms due to changes in their business models, others will lose value to other firms because of business models that have become less competitive or outdated. The mobile phone industry summarises very well these different phenomena. Nokia has been a long-standing incumbent in the mobile phone industry and did not realise that new entrants such as Apple and Samsung would become central players. With time, value creation moved away from the hardware, and as a result, Nokia's business model would not be able to create value as its vital mechanism for value creation was negatively affected by the new entrants.

Conceptually, business model innovation is the construct that has been developed to explore the relationship between value migration and business model (Kim and Min, 2015). Business models tend to change over time for many reasons, and therefore business model innovation is defined as the change in operations and value creation that leads to an improvement in business performance. Theoretically, there is a lack of clarity about what business model innovation is. Indeed, some authors suggest that business model innovation is creating a new business model (Zott and Amit, 2007) while other authors point out that small changes in the business model qualify as business model innovation. The two perspectives are summarised by Massa and Tucci (2014), who suggests that business model innovation refers both to new business models developed by new companies and to changes in the existing business models. Another element of ambiguity in the literature refers to the scope of business model innovation, although there is an agreement that at least one dimension has to change radically before the change can be qualified as innovation.

Business model innovation follows value migration: changes in business models might be needed when there are structural changes in industries (Johnson and Suskewicz, 2009); in these cases, firms need to think how they create and capture value by identifying the best business model that allows keeping creating value when this is migrating between firms. A company that has successfully changed the business model following technology disruption is Netflix. The company started as a rental company for DVDs which became quickly successful in its line of business. However, as streaming services started to emerge, the company successfully jumped into this segment of the video industry. Two critical elements of the business model had to change: the products offered by the company and the pricing structure.

4.3. Business Model Innovation and AI

The previous paragraph clearly shows that even established businesses can fail if they do not change their business model continuously (Achtenhagen et al., 2013). While this is true for any new technology, it is particularly relevant in the case of AI. The diffusion of AI in an industry tends to trigger value migration across different segments of the industry: it does so by facilitating the emergence of new businesses that use AI not only to reduce the costs associated to production (through automation, for instance) but to change the mechanisms through which value is created and delivered. Still, the role of AI in driving business model innovation has been explored only recently. The focus is mostly on new entrants (like Uber and Airbnb) and their business model.

However, the effect of AI on business model innovation goes far beyond that. Besides enabling business model innovation by facilitating the entry of new competitors, AI technologies can also change the relationship between the different components of incumbents' business models. We argue that to understand business model innovation following the adoption of AI, we need to explore the mechanisms that connect different components of the business model and how these change due to the deployment of AI. Three main dimensions to business models have been identified: value creation, value delivery and value capture.

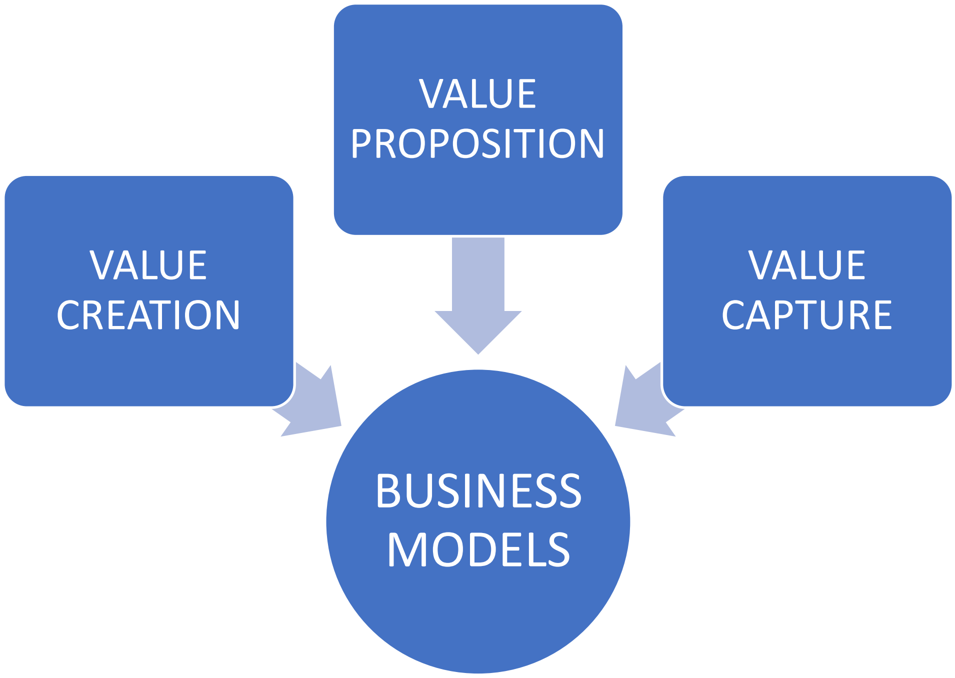

Figure 2. Basic elements of a Business Model.

Value creation and delivery focus on customers and how they are engaged while value capture refers to how value is monetised. Therefore, to discuss business models, we need to focus on these dimensions, and so we explore what it means for business model innovation and its relationship to technical innovation.

4.4 Business Models Innovation and AI: A Taxonomy

The current literature on business model innovation focuses on external antecedents linked to changes in the business environment (Amit and Zott, 2012). So far, very few papers have explored the role of technology, and it is only recently that the introduction of new technologies has been studied as a factor driving business model innovation. Work on classifying business model innovation and technology has proceeded along two lines. On the one hand, some researchers suggest that technology can be incorporated into a business and have a positive impact on performance (e.g., Amit and Zott, 2001; Zott and Amit, 2007; Osterwalder and Pigneur, 2010). On the other hand, some other authors see the concept of a business model as separable from technology (Teece, 2010 or Baden-Fuller and Morgan, 2010). However, there is no such empirical work in the case of business model innovation driven by AI. Therefore, we will provide a taxonomy of the new business models that have emerged because of AI-based on the qualitative literature on AI and business model innovation.

There are many more examples of businesses that use AI to reduce costs or boost their revenues. Can we identify some patterns around the different types of business model innovations that employ AI? To study the impact of AI on business model innovation, we use the framework developed by Osterwalder and Pigneur: therefore we describe for each type of impact the effects of AI on value creation, value delivery and value capture. This way, we identify four ways AI can change the elements of the business models. We start from an incremental change going to a radical transformation of the business model, which implies a change of all the business model elements (see Fig 3). Importantly these four models are not mutually exclusive, and businesses can employ them simultaneously. Besides, business model innovation will be studied in the context of incumbent firms that prefer to reconfigure the elements that constitute their business model because of AI's introduction. In other words, we are not interested in the business models of new entrants. In general, we also want to distinguish incremental business model innovation (where businesses tend to keep the same customer base while expanding their activities in such a way that new customers are attracted) from radical business model innovation (where businesses leave behind the core of their activities and move to new markets).

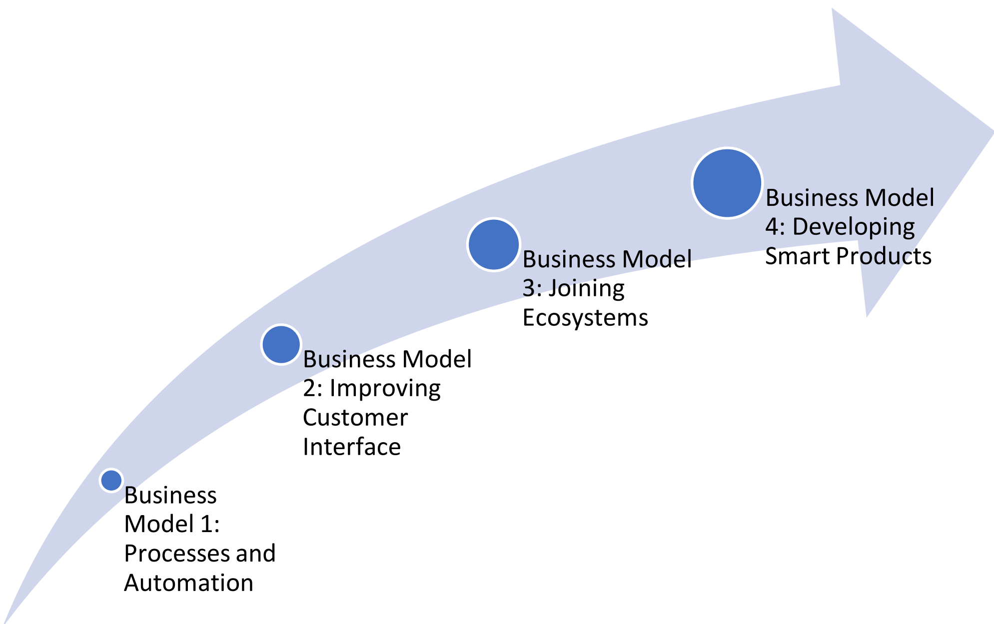

Figure 3. Four AI driven business models.

4.4.1. Processes and Automation

In this case, AI is mostly used by businesses to improve internal processes without changing the whole business architecture. The main goal of the business is to increase efficiency, and it does so by automating processes. Relationships with suppliers, for instance, can be streamlined through the use of bots. Overall, the emphasis of this type of business model innovation is on automating existing processes to capitalise on the company's existing knowledge and resources. The automotive industry is the best example: robots have been used for a while in the assembly lines of companies such as Jaguar-Land Rover and BMW[12]. In this case, value creation is generated by better connections among machines, increasing efficiency of the workforce and transparent management. Efficient use of internal resources is the crucial mechanism for both value capture and value delivery to customers. Finally, value capture is driven by more efficient processes and use of resources.

4.4.2. Improving Customer Interface

AI is deployed to understand customers and their needs better. Virtual reality and bots are the key technologies here, and they follow the initial investment in automation in the sense that they allow businesses to capitalise on the increasing efficiency of their internal processes. Value delivery is facilitated by segmentation (based on data analysis) and the resulting development of long-term relationships with customers. Besides, digital distribution channels can improve consumer sales. At the same time, new services can be created as consumers needs can be easily identified, thanks to the extensive use of data collected through bots. Finally, new services (like dynamic pricing or pay-per-use) generate new revenue streams that allow businesses to capture value. Examples include supermarkets (Tesco, Sainsbury's) and large retailers (Boots) which use data collected through loyalty cards to segment customers and personalise offers based on their characteristics and preferences. Other examples include Spotify and KFC, which use AI to improve their relationships with customers (Soni et al., 2019).

4.4.3. Joining Ecosystems

AI facilitates creating virtual marketplaces that allow businesses to develop new services and create new value networks (Adner and Kapoor, 2010). In these examples, AI allows integrating knowledge and resources drawn from many organisations and businesses into networks that allow delivering new services or new products to the consumers or other businesses. In this business model, value creation is generated by using real-time information about production, sales and availability of new services. Value delivery is guaranteed to all the businesses that belong to the network by delivering the new services that are intrinsically linked to the platform's presence. Finally, value capture is guaranteed by the revenue streams generated by the new services. The virtual marketplace, which Amazon enables, is the prime example of such an ecosystem; however, other examples include the Appstore or Google Playstore.

4.4.4. Developing Smart products

AI allows them to develop and commercialise different goods and services, allowing firms to diversify or expand their markets. The emphasis is on the development of AI-powered products which are the critical mechanism for value creation. Importantly, customers are part of the value creation process, and there is a direct relationship between the business and the customers, thanks to AI. Value delivery is generated by the smart products and the innovation in the associated services while value capture is generated by the new revenue streams associated with the new products. All products for smart homes or cars use AI and tend to interact with customers to deliver services tailored to their needs.

4.5 General Considerations

There are some expected benefits associated with most AI technologies, namely real-time capability, interoperability and the potential of integrating production systems:

- First, they tend to lower the production costs, which may result in low prices that may be eventually passed on to the consumers. This is an inherent feature of AI that generally tends to replace labour and, therefore, reduce a large share of businesses' variable costs.
- Second, AI allows businesses to generate new products and services; while it is true that some of these can be "intelligent" variations of existing products, importantly some of these products are innovative in the sense that they did not exist before the advent of AI and they only do so because of AI.
- Third, AI can change the nature of the interaction between consumers and businesses. In the past, consumers' role was that of passive purchasers of goods that could express their preferences only by walking away from specific products.

As business models change with the advent of AI, consumers tend to drive the production of services, and in some case, they are co-producers of services and products. Their preferences get known to businesses at an early stage and businesses can get a detailed picture of consumers' preferences; this can lead to the development or creation of new products and services that better address the consumers' needs. In this respect, embedding AI in a business model provides opportunities to create new value delivery mechanisms that better address customer needs. AI allows creating two-sided value delivery systems that distinguish between two types of customers: those that provide data that allows personalising the services that are eventually offered to the second group. In other words, the notion of customers as being just at the end of the value chain and willing to pay for the products has changed.

Simultaneously, while personalisation of services and products is highlighted as one of the strengths of the AI-powered business models, in real life, we can observe businesses that offer "one-size-fits-all" value delivery proposals along with personalised offers. In these cases, scale matters and the business model have to find the right balance between the two types of services.

So, the AI business model has to deliver value to the former group so that the latter can have better services. Implicitly this requires the development of two parallel mechanisms for value delivery. In practice, the two mechanisms can support each other and connections between the two mechanisms matter as they eventually define the mechanisms through which value is captured. Typically, value capture is rationalised in terms of pricing and price discrimination. However, the critical feature of business models that embed AI is that pricing is not the only mechanism to capture value, but it is one of the many that businesses can use. For instance, the use of the consumers' data to personalise offers can be alternative mechanism companies can use to capture value.

AI-driven business models tend to be responsive to user-driven design and, as a result, business models tend to be better aligned to customer value creation. However, businesses need to develop the technical capability to acquire data about their clients and start to think in terms of ecosystems rather than value chains. Additionally, AI is pushing companies to a change from product to service mindset. This outcome is not new in itself. Products are delivered as a service as the digital part of a hybrid solution. The result is the so-called product-service system concept that shows how development and offering of specific product-service bundles are sold to customers as a solution rather than a product. This practise is widespread in the automotive industry where smart products are sold together with smart services, and as a result, suppliers, customers, and other partners become part of a networked ecosystem (See Dinsdale et al., 2016 for a discussion).

AI allows the horizontal and vertical integration of the value chain, allowing expanding the firms' boundaries. In this context, new actors arise, and there are new ways of creating value using ecosystems that go beyond individual value chains. Openness can create communities with similar interests and therefore monetise innovation through other routes (Dahland and Magnusson, 2008). Openness can let users indicate what they want and allow them to be engaged with the business, leading to value creation for both sides. For instance, firms contributing to online communities share their adaptations with vendors, which will improve the next release.

One key question is whether business models that embed AI at their core can be easily imitated. It is an important question because if they are not easily replicated, they can generate a higher return to AI investment until they are. In reality, this is not always the case, and businesses have to find mechanisms that allow them to capture value even when imitators enter the industry.

4.5 Choosing a new business model

The value migration framework only suggests that firms must pursue business model innovation to remain competitive. Of course, it is still unclear under what conditions business model innovation takes place. Business model change is an experimental search process where elements of the existing business model change in a progressive way (Sosan et al., 2010; Berends et al., 2016). From the perspective of established businesses, changing an existing business model can be problematic, and the existing characteristics of the business model tend to limit the choices available to firms. As a result, the mechanisms for value creation, delivery and capture may change as businesses have norms, behaviours and organisational structures they must modify as they adopt new business models. The term "institutional logic" has become very popular in this context (Thornton and Ocasio, 2008). Thornton and Ocasio (2008) integrate previous work on institutional logics (Friedland and Alford, 1991; Jackall, 1988) to propose a definition of institutional logic that helps to understand individual and organisational behaviour in social and institutional contexts.

According to the theory, changes in the existing business model require exploration and experimentation (Andries et al., 2013; Chesbrough, 2010; Sosna et al., 2010; Bojovic et al., 2018). Business model innovation is essentially a learning process (Chanal and Caron-Fasan, 2010; McGrath, 2010; Sosna et al., 2010) which has to consider how the environment has changed (Moingeon and Lehmann-Ortega, 2010). While experimenting with new business models is a routine process[13], it is particularly vital in AI as this is an emerging technology that is poorly understood. Indeed, experimentation allows businesses to acquire knowledge about how the new technology works and allows to manage risks (Andries et al., 2013; Berends et al., 2016; Chesbrough, 2010; Gelhard et al., 2016; Morris et al., 2005) by helping managers to select the best business model given the capabilities of the technology and the constraints posed by the environment. For instance, a company may want to use AI to offer customers a set of personalised services based on subscription. In this case, the company must understand whether the AI tool employed for personalisation is "fit for purpose" and whether the customers are open to such an innovation. To do so, the company may need to experiment with the AI tool and test how it is useful in creating and capturing value (i.e. whether it is accurate in identifying what customers may want and whether customers are happy with such innovation). Importantly, this type of experimentation may allow businesses to know about the technology's technical characteristics and how the workforce, consumers, and suppliers will accept a particular business model where AI plays a key role.

Experimentation should have a long term view and consider the fact that several initiatives need to be tested and combined so that they can jointly produce value. For example, to allow AI tools to segment customers efficiently, a company might need to set up several sales and marketing initiatives and check which ones can deliver value fast. [14].

Text Box

Challenges that businesses face following the introduction of AI in their organisations have been illustrated by several studies that focus on specific case studies. Interesting case studies are presented by Lee et al. (2019), Semmler and Rose (2017), Jia et al. (2018), Fountaine et al. (2017). Additional examples of how AI is used can be found in Marr (2019) and Patrizio and Maguire (2019),

A few examples of companies have started to use AI to change some mechanisms they use to either deliver value to customers or create value. Examples include:

- *Haidilao is a significant chain of China's hotpot catering industry. Haidilao opened three new technology restaurants in 2019, including robotic arm and robots serving food and smart kitchens. More than 1000 robots were installed, and Haidilao pointed out that innovative technologies such as food delivery robots and kitchen cleaning robots have enriched customers' dining experience. Simultaneously, intelligent robots' application reduces employees' working pressure and makes their work more comfortable so that employees can better serve customers.*

- *Experian uses data from marketing databases, transactional records and public information records and has embedded machine learning into their value proposition.*
- *American Express and Lloyds Banking use machine learning to detect fraud near real-time and reduce their losses.*
- *Volvo uses machine learning to predict when parts would fail or when vehicles need servicing.*
- *Press Association have robots write 30,000 local news stories each month in a project called RADAR.*
- *Alibaba is an e-commerce platform which uses AI to improve the efficiency of its payment services. It is planning to integrate its traffic control and transport billing into its AI ecosystem. Alibaba has focused on the development of AI products following the creation of the AI labs in 2016. For instance, the interactive assistant Ali-Genie is a product of the labs.*
- *Toutiao is a Chinese platform created in 2012 and uses AI to recommend users' content, based on their interaction with the platform.*

Source: Jia et al.(2018)

Some researchers have advocated running multiple business models when pursuing new opportunities[15]. For instance, Universities may have moved into the online delivery model (secondary business model) simultaneously as the traditional face-to-face delivery model (primary business model). Some others have pointed out that by running parallel business models, the firm may not see complementarities between them (Markides and Oyon, 2010; Markides, 2013) and is often the leading cause for failure (Porter, 1980; Casadesus-Masanell and Ricart, 2010, 2011; Casadesus-Masanell and Tarzijan, 2012). Alternatively, businesses can change the primary business model in line with the second business model (Bock and George, 2014; Berends et al., 2016). In this case, the firm can transform the primary business model elements in line with changes in the external environment (Achtenhagen et al., 2013)[16].

Changing a business model requires businesses to acquire knowledge about new technologies and changes in the environment. A lot is known about how businesses go about acquiring new knowledge. Researchers have pointed out that knowledge can be sourced externally, and that competitive advantage can be created by combining external knowledge with internal knowledge. There are two types of knowledge acquisition activities: exploration and exploitation (Gupta et al., 2006; Raisch et al., 2009; Osiyevskyy and Dewald, 2015). Exploratory knowledge acquisition aims at developing new competencies[17], while exploitative knowledge acquisition wants to expand existing knowledge[18]. The two activities can complement each other, and indeed, ambidexterity has been proposed to combine the two strategies for knowledge acquisition (e.g., Birkinshaw and Gibson, 2004; He and Wong, 2004; Andriopoulos and Lewis, 2009). External and internal knowledge can be combined (e.g., Chesbrough and Appleyard, 2007; Frey et al., 2011; Laursen and Salter, 2006; West and Bogers, 2014) and can be acquired through alliances or collaboration with other organisations. Collaboration can be a fruitful source of knowledge which quite different from the business' current knowledge base. Once embedded into the firm's knowledge base, it can eventually lead to a change in the business routines and the business model (Kortmann and Piller, 2016; Monteiro et al., 2017). In practice, we do not have results on how businesses acquire AI-related knowledge although we can assume that an ambidextrous strategy can help firms capture external knowledge that allows deploying AI efficiently (O'Reilly and Tushman, 2008). The more advanced this capability, the better firms are at coordinating and integrating AI-related knowledge into their business operations (Kraaijenbrink, 2012; Subramaniam, 2006).

Reim et al. (2020) have highlighted the changes that need to occur when trying to innovate their business model. The authors use the concept of digital transformation to clarify that these changes are not simple IT initiatives but rather a re-design of the business activities to align AI strategies to the overall business strategy. In their view, this type of changes can lead to new business scope and customers. They also highlight the importance of organisational aspects when changing a business model. Pilot projects can help identify organisational bottlenecks and the additional actions needed to ensure employees support and accept the AI tools. The importance of intermediaries between data scientists and business managers has been highlighted by Reim et al. (2020) and by Fountaine et al. (2019): both suggest that technologists are needed to demystify what AI does and give managers assurance they are still in control. In some sense, the emphasis on intermediaries' role in this field highlights the fact that the current provision of skills among general management cannot easily support business model innovations driven by technology. There is an extensive debate on skill shortages in data science (Soni et al., 2019), but there is not much discussion on the managerial skills shortages in this area. This topic can be a primary area to study in the future as AI becomes more ubiquitous than it is now.

5. Business Model Innovation and AI: The Role of Platforms, Standards, Ethics.

In Section 4, we have presented the different business models that make extensive use of AI as a component of the mechanisms to create, deliver and possibly capture value. In this section, we plan to introduce several industry-level factors that may influence the choices that businesses make in the new business models. In particular, we focus on:

a) the structure of the technology industry and the nature of competition in such industry;

b) the presence of technical standards and

c) last but not the least the ethical framework adopted by the businesses about the uses of AI and validation and maintenance.

Of course, our list is not exhaustive, but it aims at identifying three key factors that can shape the choices made by businesses concerning the new business models. In our discussion, we will only discuss the impact that each factor has on the business model's choice (see Fig. 4) although, in reality, we cannot exclude the possibility that two drivers can affect each other. However, this possibility is beyond the scope of the analysis.

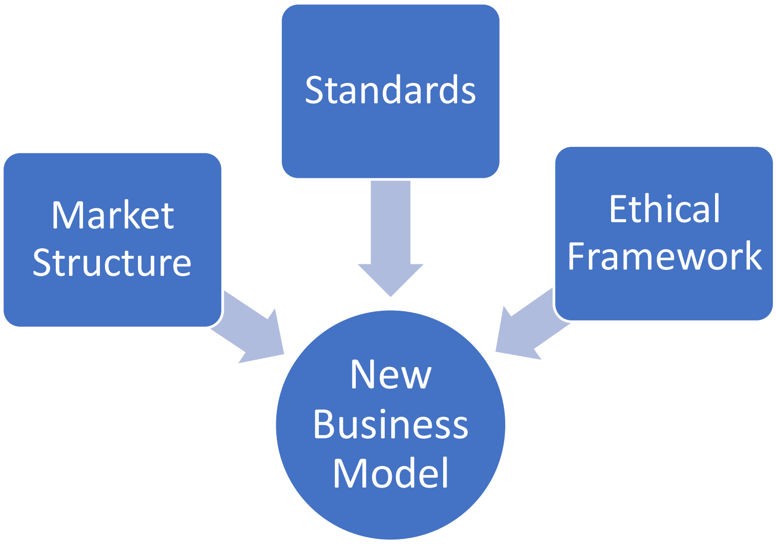

Figure 4. New Business Model and Its Drivers.

5.1 Platforms and Industrial Structure

One important conclusion from our previous analysis is that technology can help businesses to capture, create and deliver value but that this is only possible as long as the technology is fit for purpose, i.e can deliver tangible benefits to businesses once it is embedded in the architecture of a business model. Of course, this implies that it is necessary to take a closer look at the technology itself but more importantly, at the characteristics of the technology industry. This result is not surprising: (very) large tech companies lead the effort to develop AI capabilities across the global economy with their business models and transparent mechanisms for value creation and value capture. In this respect, whether the technology is fit for purpose is very much a result of how the tech companies decide to compete in this arena.

As mentioned above, critical development in the AI industry is the growth of AI-as-a-service where AI capabilities are offered as part of platforms such as Watson or Google Machine Learning. In some sense, this new development is not unexpected. Large tech companies have established the "platform" model - which relies heavily on direct and indirect network effects to grow - as a very successful mechanism to create and capture value: ultimately the whole digital economy relies on platforms and the associated eco-systems of users to deliver and capture value (Parker and Van Alstyne, 2005; Van Alstyne et al., 2016; Parker et al., 2016). Platforms allow to gather information on users efficiently and allow to create markets where services and products are exchanged. In turn, platforms facilitate the creation of platform-based businesses whose primary purpose is to facilitate transactions between other businesses and consumers and help generate eco-systems of interdependent businesses (Zhu and Furr, 2016; Zhu and Iansiti, 2012; Adner and Kapoor, 2010). While some authors argue that platforms are different from eco-systems [19] in reality, they share some standard features. They both rely on interactions between the digital medium and many users, and in reality, most of the value created by platforms is in the number of interactions. Some interactions are bi-directional (where more organisations are part of the interaction) while some other interactions are not. In both cases, companies interact with users and extract value from these interactions outside their boundaries. The platforms deliver consistent components, define common interfaces as well as the technical standards. Therefore, they create opportunities for businesses and developers as they offer AI-related services at a fraction of the cost. Eco-systems can become very complicated quickly as they tend to add more partners as they grow (Gawer and Cusumano, 2014). In these cases, platform service providers act as platform manager or orchestrator and therefore act as a central business interacting to various degrees with the members of the network and using the platform as users. Of course, all this is possible because the costs of storage and data processing have dramatically fallen due to the introduction of cloud computing.

As the platform provider becomes the orchestrator of the eco-system (or of the network) (Rochet and Tirole, 2003; 2006), they provide an environment where software is integrated, and access to training data is guaranteed well as labelling services and consulting. In other words, platform providers tend to offer an environment where products can be standardised, although still differentiated from those of the competitors. In this area, AI services allow platform providers to provide a set of highly specialised services that are cheap to maintain given access to training data and hardware.

What are the implications of all this on the market structure?

- It is essential to clarify that companies' size in the technology industry does not necessarily imply a concentrated industry. In the case of platforms, a platform owner's main objective is to maximise participants on the two sides of the market. As a result, the platform owner will always increase users' number (whether paying or not) of its platform. Therefore, platforms change the efficient minimum scale for the large technology companies that have been able to scale up rapidly by collecting information on their users and creating new services to businesses and AI developers. So, the cost of doing business has lowered, and these firms' size reflects this fact. In this respect, switching costs are a better indicator of competition, and while in the past researchers had assumed there are no switching costs when dealing with platforms, in reality, this is no longer the case. In the current environment where platforms provide AI services, switching costs can be very high as the availability (or lack of) training data may make a business less likely to switch to other platform providers.

- Availability of large training datasets is quite essential to businesses that want to use AI systems. Search engines embedded in platforms collect data on their users' behaviour, which can be used as training data for AI. Thus, for other firms to benefit from AI, they need access to platforms with a large user base and the data that come with it. Access to training data may act as an entry barrier for new competing networks at the industry level. Also, existing networks can take advantage of their monopoly positions to discourage innovation from new entrants. A related concern is an impact that concentration of data among a few dominant platforms may have on the AI system's quality and even their use (Brundage et al., 2018).

- High switching costs and the nature of competition of technology markets narrow down the options that incumbent firms have in business model innovation. These issues may not be relevant to firms that have been built on platforms since the very beginning (Pitelis, 2009; Pitelis and Teece, 2009; Rindova et al., 2012). Such business examples include Uber and Airbnb, which both started as platform businesses (Evans, 2016), and their main challenge is about gaining legitimacy in the eyes of customers. However, in the case of incumbents, this may be an issue as mature businesses may have to decide what mechanisms for value creation, delivery and capture they may want to adopt given that their access to AI services is controlled by large tech companies which act as platform orchestrator. The literature has pointed out that in practice platforms induce businesses to privilege business models characterised by openness (Casadesus-Masanell and Zhu, 2013). Business models that use AI at their core require businesses to access AI services through platforms and interact with many organisations that use the platform. Therefore, businesses have to learn to manage a much larger number of interactions across the whole value chain, i.e. not only with suppliers and customers. For instance, in product development, interactions with users through open innovation and innovation contests become common. Equally, the quality control function may be outsourced as businesses may rely on platforms to collect data on the quality of their products and services. External focus requires businesses to develop additional capabilities that help manage these new types of relationships and interactions with organisations that cannot be traditionally considered to be stakeholders.

- Openness means that the business has to accept inputs from outside the traditional boundaries of the business. Examples include open innovation where innovation is developed collaboratively with inputs from across many external organisations (Kafouros and Forsans, 2012). The shift towards openness requires a change in culture and internal processes so that externally sourced inputs can be successfully integrated into the new business model; more importantly, openness results from platforms dominating the technology industry's structure.

Welfare considerations. To conclude this section, we want to offer some reflections on the extent to which the nature of competition in technology markets is welfare-enhancing. It can be argued that the platform model adopted by tech firms may foster competition (at least among users) by inducing businesses to adopt business models characterised by openness. Empirically, we do not have any evidence on the magnitude of these effects even if they are theoretically plausible. A related issue is whether the platform model can enhance innovation among tech firms. Existing work on competition and innovation points to the existence of two counteracting effects (Aghion et al., 2019 for a summary of this literature): on the one hand, more intense product market competition (or imitation threat) induces firms at the technological frontier to innovate in order to escape competition; on the other hand, intense competition tends to discourage firms behind the current technology frontier to innovate. Which of these two effects dominates, in turn, depends upon the sector. The implications for the development of AI may be interesting. As entry costs into the technology markets become larger and larger (as the availability of training data acts as a barrier to entry), it is unclear whether companies that invest to be closer to the frontier may be interested in continuing to do so as it may be more profitable to work on AI application rather than on theoretical developments in AI.

5.2 Technical Standards

Academic research tends to assume that radical innovation (like AI) will lead automatically to improved business performance (once the new technology is embedded in the existing business model). Therefore it tends to ignore the interdependencies between business model choice and technology. However, technology has to operate with other technologies and therefore, it may create value if they work well (Eisemann et al., 2011). Interoperability is essential in particular if we consider platform technologies as they offer opportunities for complementarities, which can enhance the value capture mechanisms (Eisemann et al., 2011). Interoperability is linked to technical standards, and in this section, we will focus on technical standards and how they support new business models that use AI.

5.2.1 Why do we need technical standards and what is their impact?

Standards can be of several types[20]. Product standards can define measurements, requirements, labels and testing methods (Blind, 2004; 2006; Swann and Lambert, 2010; Swann, 2010). Management process standards can describe processes to achieve goals such as quality[21] or functional safety (processes to assess risks in operations and reduce them to tolerable thresholds) (Blind et al., 2011). Network-product standards that support interoperability and network-process standards are used to grow their market size and reduce their costs (Cihon, 2019). Appendix A discusses the bodies that develop standards.

Most of the literature on standards has focused on industry players' rationale to introduce standards and their impact (Narayanan and Chen, 2012). At a fundamental level, standards are introduced to reduce asymmetric information between buyers and sellers (Swann, 2000; Blind, 2004; Swann and Lambert, 2010). Asymmetric information is familiar to most markets, and it arises every time the seller has more information about the quality of a product than consumers. To understand how standards work, consider the incentives of economic agents and the objective of standardisation process (Blind, 2002; 2004; Swann, 2010; Swan and Lambert, 2010): in a world, characterised by uncertainty about the quality of the products, standards can make explicit the production process and clarify to users the specifications of the products as well as the processes followed for their production (Swann, 2000; 2010).

A different classification is proposed by Cihon (2019). He suggests that standards generate network externalities for the businesses in the industry; in turn, these may become engaged in a coordination game where economic agents are incentivised to cooperate[22]. In this case, standard bodies may be necessary to create the standards, but they are not necessary to maintain them as the need to coordinate will give economic agents the incentives to coordinate their activities (Cihon, 2019)). These standards have been labelled by Cihon (2019) "network standards." Other types of standards are the "enforced standards", according to the author. These may take different forms from regulatory mandates to contractual monitoring (Cihon, 2019). Certification of adherence to a standard is a method of enforcement that relies on third parties. Self-certification can also be used, where a firm will claim compliance and accept to be monitored in the future (Cihon, 2009). In these cases, monitoring can occur through periodic audits, applications for re-certification (Cihon, 2009).

There are other benefits associated with the use of standards and authors such as Swann (2000; 2010) and Blind, 2004; 2006; 2013) have provided the following list of arguments:

Facilitating inter-operability of products and processes. According to Blind (2013), standards will support interoperability between products. As an economic phenomenon, interoperability directly benefits the consumer as it reduces switching costs. For instance, switching costs may lock in the customer and stop her from changing suppliers limiting competition in the industry (Farrell and Klemperer, 2007). Conversely, by reducing the switching costs, standards can encourage competition by facilitating changing suppliers, improving choice, and lowering the customer's investment cost. Another benefit of interoperability is that it allows producers to exploit network effects associated with technologies whose benefits are a direct function of the number of users. In these cases, the larger the number of users, the larger the benefits that accrue to producers and therefore, producers have an interest in ensuring interoperability as it may increase the size of the total market. Significantly, consumers can benefit as well as interoperability implies that they can choose among different products that are all compatible with each other.

Efficient reduction of a variety of goods and services. Standards align the expectations of buyers and sellers. Importantly, standards make information on products available to all other firms and consumers by facilitating efficient and exchanging information (Swann, 2010; Blind, 2013). The result is that each transaction's costs are lowered and therefore outsourcing the variety of goods is aligned to what consumers want (Swann, 2010). Significantly, management standards can help support this function as they can help companies improve their efficiency and performance and reduce errors and defects. As a result, costs are reduced while providing consumers with more certainty about the products' quality.

A few studies have tried to clarify the impact of standardisation on innovation. These studies have been summarised by Swann (2000; 2010) and Blind (2002, 2004, 2006, 2013); they have provided comprehensive surveys of the literature on innovation and standards. One way to formalise the impact of standards on innovation is by considering standards as a mechanism that reduces the current and future transactions costs (Swann, 2000). Besides, standardisation is a framework within which future standards can be produced (Goluchowicz and Blind, 2011). In this respect, it limits the variety of options and induces firms to develop credible technologies in the eyes of the consumers and can support the development of complementary technologies. From the innovator's standpoint, the presence of standards in the market justifies the investment to produce the new products at scale (Swann, 2000; 2010). This way, businesses can generate profits which can let them reap the benefits of the initial investments. Importantly, standards may create trust in new products, leading to acceptance among consumers by making it clear to consumers how risks have been mitigated (Blind, 2009). Although some economists have suggested that standards may slow down radical innovation (Katz and Shapiro 1992), standards can avoid these lock-in effects and compatibility over time is ensured (Swann and Lambert, 2010). Additional benefits of standardisation for innovative firms include:

- **Development of a critical mass of innovators in emerging industries.** Standardisation may create a critical mass of innovators in emerging industries and promote innovative products (Blind, 2016). In particular, in networked industries, standards allow the development of complementary innovations (ISO, 2011, 2012).
- **Diffusion of technical information.** Standards clarify that innovation has the features that producers claim are there and that it is safe to use it (Narayan and Chen, 2010; Blind, 2013).
- **Diffusion of best practice in industries.** Standards help firms diffuse best practice in manufacturing and technology while allowing first-moving to gain some benefit from licencing standards (Simcoe et al., 2009). Besides, standards can set the minimum requirements for environmental, health and safety impact of new products.
- **Increase competition in an industry.** This effect works in two ways (Lambert and Swann, 2010). On the one hand, standards can generate competition among technologies that can benefit the economy as a whole. On the other hand, technical standards can level the playing field among businesses in the industry.

5.2.2 Technical standards and AI

There are two areas related to AI associated with the development of technical standards (Cihon, 2019). The first area is around AI safety[23], and the second one is around AI systems capabilities. The field of AI safety is young, but given its potential impact on the future developments of the technology and its industrial uses, standards need to emerge relatively quickly. One of the critical issues in implementing safety processes at scale and this issue needs to be developed into research on technical safety itself[24]. A starting point would be the existing safety standards for emerging technologies as developed by international standards bodies. The best way forward is to develop the current best practice and develop a set of processes enshrined in a standard that helps researchers develop a checklist before undertaking research (Cihon, 2019). The process standards could contain the exact specification of the code and the assurance and validation methods (Cihon, 2019). Finally, the best practice could establish how to monitor standards and define the thresholds above which risk can be considered so high that different procedures need to be taken into account to ensure the developed AI's safety (Cihon, 2019).

According to Cihon (2019), examples of standards for AI include:

● Foundational Standards: Concepts and terminology (SC 42 WD 22989), Framework for Artificial Intelligence Systems Using Machine Learning (SC 42 WD 23053)

● Transparency of Autonomous Systems (defining levels of transparency for measurement) (IEEE P7001)

● Personalised AI agent specification (IEEE P7006)

● Ontologies at different levels of abstraction for ethical design (IEEE P7007)

● Well-being metrics for ethical AI (IEEE P7010)

● Machine Readable Personal Privacy Terms (IEEE P7012)

● Benchmarking Accuracy of Facial Recognition systems (IEEE P7013) Enforced - Product.

● Certification for products and services in transparency, accountability, and algorithmic bias in systems (IEEE ECPAIS)

● Fail-safe design for AI systems (IEEE P7009) SC 42 is likely the more impactful venue for long-term engagement.

Another area of AI where standards are necessary is related to the assessment of system capabilities. This standard is necessary to support the validation of AI systems beyond the areas of safety. Performance benchmarks already exist for specific tasks. The **AI index** reports developed by Stanford University on the AI performance annually, and there are benchmarks in place (like the **ImageNet corpus[25]** and the General Language Understanding Evaluation project[26]) which though need to be assembled into a broader capabilities framework.

The importance of creating technical standards in the context of AI development is clear to all interested parties (Tassey, 2000; Simcoe et al., 2009) and the arguments in favour of their introduction are well-rehearsed:

- **Communication among researchers and policy-makers.** The development of technical standards can facilitate communication among the number of institutions and bodies working in the field. This is a notion that underpins the concept of standards according to several authors. Indeed, both Swann (2000; 2010) and Blind (2006) suggest that standards are devices that codify organisations' tacit knowledge. Codification is useful for the diffusion of the technology which relies on exchanging what could be otherwise tacit knowledge (Swann, 2000). In the case of AI, standards may facilitate communications, facilitating the development of trust (Cihen, 2019). In this respect, standards may act as a mechanism to retain the benefits of private investment in the new technology mitigated by public intervention benefits. The standardisation process can facilitate the diffusion of technical information.

- **Coordination.** Technical standards are a crucial mechanism to coordinate producers' activities along the supply chain and ensure interoperability among the several components. Standards elaboration allows industry players to select relevant knowledge and technologies and avoids industry fragmentation. Blind and Gauch (2009) suggest that standards are a channel for knowledge transfer through a consensual process (see also Bozeman (2009) for a similar point). This way, R&D results can become public goods through standards that are accessible to everybody and are broadly implemented because all industry players have reached a consensus on their content (Farrell and Simcoe, 2012).

- **Time to market and future developments**. Standards offer several opportunities to the AI's growth by reducing the time to market for inventions and technologies (Blind, 2006). Using the arguments developed by Blind et al. (2011), there are four main channels through which standards enhance the development of Artificial Intelligence:
    - Standards can minimise coordination costs. These can be important for the development of technologies that work as platforms to host apps.
    - Standards allow firms to exploit economies of scale. Indeed, standards allow developers to access
    - Standards can increase the demand for complementary products and services that can be routed through the AI-powered platforms.

Standards provide the institutional framework that allows companies to develop new technologies in a controlled and safe manner, which is very important in the context of AI, which can be deployed across several industries and several applications.

The standard approach to the growth of an industry around new technology is based on public funding of R&D and IP rights. The assumption is that increases in publicly funded R&D and a robust IP regime may facilitate the private sector investment in AI. In the context of AI, however, it is questionable whether this is the case. Indeed, the development of AI technologies is a very diffuse process that involves many actors, which makes it necessary to develop effective mechanisms for fast technology transfer. In this sense, standardisation can be such a mechanism and help the process of knowledge diffusion, which underpins the AI industry's development (Swann, 2010). Also, in the context of AI development, users are an important actor within the innovation process and standards can be used to coordinate the activities of several actors and stimulate future research in AI. Additional standards may be used to shape the R&D process, emphasising safety and the development of an ethical framework. Standards may provide information about other businesses which may lead to the development of other standards in the future and to identify the most efficient technology that may lead to the development of advanced AI systems.

- **Interoperability and international cooperation.** Standards promote the option of outsourcing of specific tasks to more efficient producers. For example, it may be optimal for a company to contract a supplier with lower input costs to manufacture their products while they focus on the design of the products (Swann, 2000). Simultaneously, by improving compatibility between components, producers can adapt products or processes according to the demand quickly. These standards may help support the growth of AI-based on systems that are implemented using consistent processes. In other words, standards may facilitate AI technology deployment, which will increase the global market for AI systems. Development of AI has quickly become a global challenge as governments worldwide have started to support AI research within their countries but with very little attention to the global landscape (Cehan, 2019). There is a risk this may lead to a fragmented governance landscape and a race to the bottom in terms of the regulation (Armstrong et al., 2013). Therefore, AI standards have to be international. Indeed, international standards have a history of guiding the development and deployment of new technologies that significantly impact society (Abbott and Snidal, 2001).

The main challenge that decision-makers face in AI standards development is how they can hinder innovation in the field (see, for instance, Swann and Lambert, 2010). According to which standards can reduce businesses' incentives to innovate, there is a long-standing view as they can limit their capability to extract a return from their initial investment in innovation (Blind, 2013; Blind et al., 2017). While it is unclear the extent to which this hypothesis is confirmed by empirical analysis (see the discussion in Blind et al., 2017), it is still an argument that underpins debates on standards in the context of AI development. Therefore, we must examine the mechanisms through which standards may impact AI innovation and eventually identify conditions under which the introduction of standards can result in an AI development slowdown.

5.2.3 Benefits of Standards for Business Model Innovation

As for the impact of technical standards on business model innovation, there is hardly any research. It could be argued that standardisation is simply a time-consuming process which produces minimal benefits to firms (Blind, 2006). It has been argued that incentives to join standardisation processes are limited because of opportunity costs as these efforts limit the competitive advantage that lack of standards offers (Swann, 2010; Blind et al., 2011).

While there is some debate on these arguments (Blind et al., 2017), standards are beneficial for early technologies that can change current business models. Significantly, compatibility standards can promote the diffusion of technologies and products in network industries. In these cases when there are emerging technology fields, standards may create the conditions to set flexible framework conditions that can be transferred into new business models that can be developed further when the technology is mature (Sinfield et al., 2012). Based on the previous discussion on the three main components of a business model (components that are arranged around the core mechanisms for value creation, value delivery and value capture), we can argue that the development of technical standards for AI can shape the design of mechanisms for value creation and value capture.

As for value creation, standards reduce costs associated with the adoption of AI and the costs of developing further AI-based applications that can solve business-specific issues. As a result, standards can incentivise businesses to adopt new business models that privilege value creation through cost reduction. As for value capture, standards allow businesses to capture value by developing new products that are triggered by the compatibility of the different components of AI. This is a departure from the traditional value capture model where protection of intellectual property and price structure are the standard mechanisms to capture value.

In this respect, an interesting issue here is about the relationship between patents and standards. One argument is that the integration between IP and standards can enhance AI innovation as it would provide businesses with more mechanisms to capture value (e.g. Blind and Thumm, 2004; Berger et al., 2012). Combining the two activities creates incentives to invest in innovation and ensures that businesses invest resources in technologies that have significant potential in terms of diffusion. These patents can then be licensed by the patent holder using the Fair Reasonable and Non-Discriminatory (FRAND) condition although Blind et al. (2017) suggest that the accumulation of licencing fees by different owners may generate increasing licencing costs.

There are many counterarguments, in any case. First, patents give the holders some temporary monopoly that the integration can enhance into standards, which may last longer than patent protection (Berger et al., 2012). Second, it would make no sense to combine patents and standards in platforms as revenue is dependent on the indirect network effects generated by further innovations that rely on platform technologies. Third, it is essential to recall that standards are produced once a specific technological specification has been selected. Whether this is the best technology, it is unclear although Rysman and Simcoe (2008) have provided empirical evidence that standard-setting organisations select successfully patent-protected technologies, which are superior to other available technologies. Finally, the integration between patents and standards may lead to conflict between the standards body and the patent holders (Bekkers et al., 2012). For instance, compliance with standards may infringe a patent which is not part of the standards.

5.2.4 The Institutional Framework: Regulation vs Standards

One of the areas of discussion on AI is whether standards (voluntarily agreed by key actors of industry) are a replacement for regulation. This is an essential topic in the context of AI given the industry structure, which spans several sectors and typologies of businesses and regulators. For these reasons, we will discuss these arguments and discuss the extent to which regulation and standards can complement each other in the context of AI. In a nutshell, the literature suggests that to support AI development, regulatory bodies may be problematic while standards can provide rules that developers can trust.

Before starting the discussion on the relative merits of regulation and standards, it is worth recalling that regulation is a coercive rule-setting while standardisation is a self-regulatory activity. The impact of regulation on innovation has been discussed in academic literature. Complying with regulations can be costly for incumbents, and therefore it may restrict their capability to innovate firms' freedom of action (Palmer et al., 1995) although it may induce them to invest in technologies that are valued by the society (Porter and van der Linde, 1995). Regulations are mandatory restrictions released and enforced by the government to shape the market environment and influence businesses' behaviour (e.g. Blind, 2004). Correspondingly, regulations refer to a top-down approach, while formal standards are typically the result of a market-driven process (Büthe and Mattli, 2011).

Whether regulation has to be preferred to standardisation depends on the maturity of the technology. Indeed, Blind et al. (2017) have highlighted that technological complexity (like in the case of AI) generates uncertainty on the best practice that should be formalised in a formal standard (Blind et al., 2017). In such environment, setting standards according to technological preferences and potentially raising rivals' costs is expected to be much difficult and standard-setting bodies may end up work around one particular standard which may not be the optimal one (Blind et al., 2017). Consequently, in highly uncertain technologies, regulation may be a better option than setting standards (Blind et al., 2017). When the technology is more mature, it is preferable to gain revenues by expanding the markets and ensuring interoperability (Blind et al., 2017).

5.3 Ethical Framework

This section will focus on the role that ethical frameworks can play in constraining business model innovation. Typically, when organisations start to invest in AI, they tend to focus on the opportunities that the investment can bring, and most of the discussion is the costs and benefits that the opportunities may offer. However, minimal effort is given to how the new technology's deployment is aligned to the current organisational thinking around ethics.

Ethics is usually thought of as a framework to mitigate the risks associated with AI's widespread adoption. Crucially, some are direct and are linked to the direct use of AI-powered systems generate while others are indirect and are linked to the stakeholders. Traditionally, these risks are dealt with frameworks which are very rooted in business ethics. However, this attempt has not been very successful for two main reasons: first, business ethics offers a framework to think about ethical issues in a business, but it does not provide criteria that can support decision-making. Second, business ethics is not equipped to deal with technologies – such as AI - that can make decisions in an autonomous way following rules that are not apparent to the users.

Companies are aware of these issues and have tried to embed ethical decision-making in the design. For example, IBM (Guenole and Feinzig, 2018) stresses that managers should be put into the position to override decisions made by AI systems if desirable, and that bias reduction should be considered in the design of AI systems, too. The European Commission's AI High-Level Expert Group stresses that AI must be "legal, ethical and robust," i.e. it needs to prevent harm, especially for vulnerable people, and take into account the broader societal risks the impact of AI on democracy and procedural justice.

Clarke (2019) has identified several principles that guide organisations when dealing with AI and ethics:

(1) Both positive and negative impacts have to be considered.

(2) AI has to complement humans

(3) Humans need to be in control

(4) Human Safety and Wellbeing need to be preserved

(5) Decisions need by AI systems need to be consistent with human rights

(6) Decisions need to be transparent, and there has to be an audit trail.

(7) Processes for Quality Assurance need to be made explicit.

(8) AI systems need to be robust and resilient.

(9) The principle of accountability needs to be preserved.

(10) A legal framework around the use of AI systems needs to be put in place.

There are additional issues around the use of AI that need to be considered. AI requires data collection, and in this respect, the ethical issues are not very different from other types of analytics. Of course, several ethical issues arise when dealing with data collected by AI systems. These data may be sensitive and personal. An example is provided by the data collected by AI-systems deployed in a healthcare context. By definition, they can be sensitive, and besides, patients may not be aware that the data are collected. Finally, the patient may feel it cannot opt-out in this situation.

For the ethical framework to support business model innovation, it is essential to go beyond the general principles established by groups of experts and by legislation and focus on AI's actual position within the business model. As a minimum, this requires each company to establish a governance framework that will support the deployment of AI internally to support new ways of creating and capturing value. So far, governance has focused primarily on privacy protection with policies for handling sensitive personal data (Hoffman et al., 2012). Typically, this has been done in the context of the legislation on privacy protection. This cannot allow for exceptions based on the requirements of industries or even single companies. However, one fundamental limitation of the legislative tool is that it cannot deal with change and transitions in a fundamentally dynamic and contextualised way. Their role is to 'frame' decisions and situations and encapsulate patterns of behaviour; not to facilitate simple steps and activities that can take on a 'unique turn' in any given situation or even present singular and unique questions for a particular case.

Some authors have suggested something similar, although in the context of ethical data collection and re-use. For instance, Richards and King (2013) suggested developing an organisational framework for data's ethical use. Hoffmann et al. (2012) recommend establishing a small decision-making body made up of representatives of business leaders, user communities, data suppliers, and technical staff to give stakeholders some control over data use.

Beyond the use of data, the development of a framework for the ethical use of AI needs to understand AI applications' specific context in a much more nuanced way. This is important if we hope to: a) consider the continually evolving nature of technology and its uses and b) 'break free' from the question of the primacy purported of either regulation or standards that permeates discussions and decisions on AI's possibilities as described above. This will require a new way to engage with and lead implementation processes. Such a premise requires two starting points. The first one is about shifting our gaze beyond a technology-driven view that, commonly, focuses strongly on either the adaptability of technology or the adaptive capabilities of actual people and stakeholders involved where humans are not just being seen as mere passive receivers of top-down decisions or 'following' actions and instructions already developed elsewhere. Such a step will require to engage with a different understanding of change involved in AI applications' design and implementation.

Such a framework requires understanding whereby people's everyday practice can gain centre stage in the process and create trust, transparency, and accountability. We will use the main news story for elaborating on our approach. As of August 2020, one of the leading news in the UK was what large parts of the British public perceived as being a 'scandal' or mismanagement in the use of algorithms to assign the final high school grades due to the cancellation of exams in the year of the pandemic (2020)[27]. Apart from many other considerations, here, it is interesting that the 'business model' adopted was seen by decision-makers as they unquestionably the most appropriate way to guarantee fairness for all students. After the U-turn, the business model is still being seen as valid by those that chose it; however, it was at least accepted that problems happened in the process of 'implementation' (BBC Radio 4, 20.08.20).

We purport that what 'went wrong' was the excessive concern with regulation and privacy preservation underestimating the role of the process around the use of the algorithm and the need to engage key stakeholders such as teachers, students and others (including Universities) highlighting early potential problems and that was essentially 'over-run' by AI [28]. For the purpose here, this example shows a fundamental flaw in the governance model around the use of the AI in education, a flaw so fatal that a potential innovation in the model used to allocate grades has been dropped by the government because of the lack of trust between main actors and the top-down approach used to introduce it.

The development of an organisational ethical framework that is flexible enough to facilitate business model innovation requires organisations to realise that AI arises in social space because of the different actors involved. In other words, AI cannot be managed, governed and sustained in any single place and thus is fundamentally distributed in nature[29]: for instance, the development of AI in a company is dominated by cross-functional teams, and each of them can be considered a stakeholder for the specific AI project (Fountaine et al., 2019); also, the impact of AI is well beyond organisational boundaries and may ripple through the local community to impact businesses, healthcare and overall well-being. This requires an alternative view of ethics to position AI, a view that identifies and recognises the participants well beyond the 'usual' suspects. In this context, it is essential to be aware of the dynamics among the different stakeholders and how micro-politics can influence AI's decision-making and legitimise views of groups that held a position of power.

An interesting approach to developing an ethical framework for AI points towards collective ethics in the shared space of action. The implication is that decisions around the use of AI cannot be made by one person only but require several individuals' contribution. In these cases, leadership is not centralised with one individual or a team, but it is distributed. There exist theories that explain why distributed leadership emerges and what benefits it offers. Distributed leadership can support the development of an ethical framework around AI while retaining sufficient flexibility for innovation. The use of this framework implies that ethics (and ethical frameworks) is defined as a collective social process emerging from the interaction of several actors. This approach highlights that members of a community have to both support and question the values and the uses around AI. Such an approach would allow companies to 'suspend judgements', thus avoiding hasty decisions and creating awareness about the increased need for a more inclusive space of action when using AI.

Fountaine et al. (2019) report an example of a company that used AI to replace the existing scheduling methodology. The existing procedure was essentially manual and based on workers' preferences and well-known conflicts of schedules. AI changed how the schedule was decided, but importantly the company allowed the planner to use their knowledge and expertise to make the final decision on the schedule. Crucially, the final decisions were not subject to managerial approval, and effectively it created a space where planners were allowed to make decisions and show their leadership in the matter. As a result, all planners adopted the tool as they felt the tool was helping them and supporting their decision-making.

6. Conclusions

Over the last five years, advances in AI technology have rekindled the academic interest into AI and its potential impact on organisations and society. While some of the academic discussion on AI tends to revolve around the technological advances, some researchers have tried to articulate the actual impact that AI can have on businesses' core competencies, and performance as a research agenda distinct from the hype surrounds the technology itself.

Summarising this nascent literature was the objective of our paper. First, we have described the relationship between AI and business model innovation and then discussed AI's impact (as an emerging technology) on business model innovation. To this purpose, we have referred to the strategy literature that describes a business model as a set of connections among the mechanisms for value creation, delivery and capture. In other words, it describes how a business needs to be organised to create value that gets delivered to customers.

More specifically, we have used the literature on business model innovation to provide a framework to explain how businesses adapt and renew their business model once AI diffuses across industries. The framework itself has used elements of organisational learning theory; prior research suggests that the process of business model innovation is a learning process, and therefore they build a theoretical framework to research into business model innovation. This framework enables us to understand better and analyse how businesses rebuild their business models in a new setting; also, it shows how businesses learn about the possibilities the new technology offers and how the perception of these opportunities shapes the choices businesses make concerning the new mechanisms for value creation, delivery and capture.

We have also pointed out that experimenting is an essential aspect of embedding AI technologies into a new business model. In other words, the process of identifying new business models requires businesses to experiment with alternative ways of changing the way businesses can generate value and can do so as long as they can learn and identify what works given the constraints the business faces. Once these learning capabilities are in place, businesses can exploit the opportunities that AI offers to businesses very quickly. We find that businesses may follow the four patterns of business model innovations (such as changing the internal processes, improving customer interfaces, joining eco-systems and developing smart products), each varying in how they use AI to deliver, capture or generate value.

Finally, the paper has tried to identify the industry-level factors that drive businesses' preference for a specific business model. First, we have analysed how the technology industry structure – dominated by large tech firms that own technology platforms offering services to both consumers and developers – induces businesses to prefer business models characterised by openness. Second, we have discussed how the introduction of technical standards acts as a tool to enhance AI adoption. AI standards development is already underway at both ISO/IEC and IEEE as they can support the diffusion of the technology. The claim here is that standards can produce expertise that may allow the industry to move towards a business model that moves away from protecting intellectual property and product differentiation as a source of revenue streams. In other words, in the presence of standards, businesses tend to choose business models characterised by alternative mechanisms for value capture and value creation that privilege volume rather than differentiation. Finally, we analyse the impact that alternative ethical frameworks may have on the preference for a specific business model.

Our analysis of the current literature on business models and AI suggests there are several gaps in our understanding of how businesses manage the challenges that the diffusion of AI generates. Although AI has become a technology of interest for most businesses, the extent to which these businesses struggle when trying to adapt their business models to the new technology is unclear. It can be argued that businesses that have been established for a while may find it difficult to accept the notion that their business model has to change, but in reality, we have no data that support this somehow educated guess. There is, therefore, a need for more research on what prevents firms from changing their business model and how they can overcome these obstacles.

Second, it may be optimal to change the business model in some cases, but still, it is not clear who can be the agent of change. Our discussion on business models suggests that managers need to be creative when dealing with the interplay between AI and new business models. Importantly these discussions require an understanding of who can facilitate change. Importantly, different groups and teams can have different perspectives on how to trigger business model innovation. For instance, technologists may understand the possibility of the technology but may miss the implications for value capture; vice versa marketing executives may not have a technology insight. In this respect, a new class of experts that translates the benefits of analytics to marketing realms may be needed (see Fountaine et al., 2019). Notably, while it is in the interest of a business to respond to the challenges posed by new technology, fostering a culture of innovation may be difficult in companies that have been established for long. In this case, it is up to the senior management to establish a culture that facilitates learning and innovation. Still, we do not have formal studies that confirm the extent to which senior management can play this role and whether other teams within the business have to support the senior management team's activities. However, this issue has been analysed in a case-study presented by Fountaine et al. (2019) who reports of a bank that aligned its AI initiative to the existing organisational culture which may have acted as a barrier[30].

Third, the current literature does not deal with the consequences of business model innovation. In other words, the current literature offers a snapshot of how businesses have changed the way they make business thanks to AI, but there is a small number of studies that tells us about the sustainability of these new business models and their dynamics over time (Ho et al., 2011). This is expected given the fact that AI is an emerging technology.

Footnotes

[1] For instance, the UK Industrial Strategy (2017) identifies AI as one of the grand challenges and the US American AI initiative (2019).

[2] This point has been made by Varian (2019) and Aghion et al. (2019).

[3] See also Boitnott (2019).

[4] Semmler and Rose (2017) discuss the case of three companies that use AI. The first company, ROSS Intelligence, uses natural language processing to perform legal research and memo drafting. The next company, LawGeex, uses machine learning for contract drafting. It compares the draft to a library of contracts and identifies uncommon or problematic clauses and missing clauses. Finally, Beagle uses AI to draft contracts, and it is targeted at non-lawyers.

[5] This section is based on Urwin (2017) and Boden (2016): both volumes are good introductions to AI and its technical aspects.

[6] Deng et al. (2009) provide an example of a training database.

[7] For example, autonomous vehicles use a mix of horizontal and vertical AI.

[8] These include IBM (Watson), Amazon (Amazon Machine Learning), Microsoft (Azure Machine Learning Studio).

[9] Image recognition services can be very cheap (i.e. the tenth of a cent per image).

[10] Factories manufacturing microchips and circuit boards are using AI-equipped with high-resolution cameras that outperform the human eye.

[11] At an abstract level, business model innovation has been defined as the "process of defining a new or modifying the firm's extant activity system" (Amit and Zott, 2010: 2) or "the discovery of a fundamentally different business model in an existing business" (Markides, 2006: 20). In line with existing research, we suggest that business model innovation can be considered an

organisational learning process (Chanal and Caron- Fasan, 2010; McGrath, 2010; Sosna et al., 2010).

[12] BMW has a cloud operating platform - BMW Services – to manage all the robots centrally. Staff have to set up workflows and monitor their progress.

[13] For example, the innovator may refine its business model by testing different external changes (e.g., customer needs) and internal (e.g., employee skills) environment.

[14] Fountaine et al. (2019) report of a retailer which wanted to use AI to optimise floor space. Eventually, they decided to experiment with the tool, and although it produced a smaller return than expected, it demonstrated the benefit of using AI for optimisation.

[15] Markides (2013) and Markides and Charitou (2004) elaborate on creating such separate business models. Equally, Casadesus-Masanell and Tarzijan (2012) suggest that companies have to run two different business models to reduce risk.

[16] These changes in a firm's primary business model are corroborated by the dynamic capability perspective which aims to explain a firm's success over time through its ability to change and adapt to the environment (Teece et al., 1997; Achtenhagen et al., 2013). The dynamic capability perspective suggests that, in order to stay competitive, firms need to adapt and renew their business models by sensing, seizing and transforming (Teece, 2007).

[17] The joint organisation of workshops with partners to increase efficiency and reduce transaction costs is an example of the exploitative practice.

[18] Jansen, Van Den Bosch, and Volberda (2006) discuss that innovation could be incremental or radical, that is, based on exploitative or explorative organisational learning. Exploitation refers to "refinement, efficiency, selection and implementation" (March 1991: 71). Exploitation is operational efficiency-oriented arising from the incremental improvement of existing organisational routines to enable the firm to realise economies of scale, and consistency by applying standardised practices across all its units. However, exploration refers to "search, variation, experimentation and innovation" (March 1991: 71). Exploration is the development of new routines to capitalise on novel environmental conditions, but more time consuming, entails uncertain results, and has a longer time horizon than refining current knowledge and extending current competencies (March 1991; Sorensen and Stuart, 2000). As explorative learning and exploitative learning are relatively contradictory and interdependent, Li (2010) suggests that such duality of exploitative and explorative learning can be essential for AI adopters. Whether there exist different patterns of business model innovation that enable businesses to rebuild the core logic of their business model when value migrates to other parts of the industry, we note that little study is available (Schneider and Spieth, 2013).

[19] In the business strategy context, eco-systems can be considered umbrella structures that encompass platform and open/user innovation strategies since organisations managing platform and open/user innovation strategies create and manage eco-systems. Platform strategies are a

specific type of eco-system strategy with a platform manager facilitating interactions between members. In eco-systems without a firm operating as a platform manager or orchestrator, individual parties interact through various mechanisms. Eco-system strategies contain structures and interactions between constituent participants (Iansiti and Levien, 2004; Moore, 1993). Eco-system strategies can exist independently of platform and open/user innovation contexts when there is no central orchestrator, or platform manager, such as in the US residential solar industry (Hannah and Eisenhardt, 2016).

[20] See Dr Vries, (1997); Brunsson and Jacobsson (2000), Jacobsson (2000), DIN (2000, 2011), ISO (2011, 2012).

[21] See Guasch et al. (2007).

[22] An exciting example of this use of the standards is provided by Berliner and Prakash (2013).

[23] ISO and IEEE have formalised standards maintenance procedures so that standards can be updated. In particular, two standards could support AI policy goals outlined above: P7001 Transparency of Autonomous Systems, which seeks to define measures of transparency and P7009 Fail-Safe Design of Autonomous and Semi-Autonomous Systems. Additionally, the Open Community for Ethics in Autonomous and Intelligent Systems (OCEANIS). OCEANIS is a coordinating forum for standards organisations and other interested organisations to discuss efforts to use standards to develop autonomous and intelligent systems further. It was co-founded by the IEEE and IEC, among other national and regional standards bodies.

[24] A good starting point would be ISO/IEC JTC 1 SC 42.

[25] I**mageNet** is an image database organised according to the Worldnet hierarchy.

[26] GLUE integrates nine distinct natural language understanding tasks into one benchmark.

[27] The British system relies on final exams to award the so-called A-levels, an educational qualification offered to school leavers usually aged around 17-18. However, the A-level exams in 2020 were cancelled because of Covid-19 and replaced by an algorithm devised by the regulator Ofqual. The algorithm used two types of data: a) the teacher's predicted grade for each student based on their performance and b) the students' rankings produced by the teacher. Also, standardisation was carried out to eliminate inconsistencies in the way predictions were made. Finally, testing found the model's accuracy to be between 50 and 60 per cent.

[28] See two exciting excerpts from BBC Radio 4 and BBC:

"The "algorithm" also suggests the sense of powerlessness felt by those students disappointed by their results. It was a "computer says 'no'" way of missing out. Now ministers and exam regulators will have to find a human way back." (Sean Coughlan, BBC, 14.08.10).

"The watchdog's efforts to maintain standards through a, now discredited, algorithm led to problems for the awarding of A-levels last week and stress for students." (Hannah Richardson & Katherine Sellgren, BBC Radio 4 Education].

[29] Fountaine et al. (2019) report the case of a large retailer which wanted to get its employees behind its AI strategy. In sharing their vision, management highlighted the role of workers who had piloted a new AI tool that inspired other workers to imagine how AI could improve their performance.

[30] In particular, the bank created a booklet that showed how combining their expertise and skills with AI's product recommendations could improve customers' experiences.

APPENDIX A

A standardisation body (also commonly referred to as a standards organisation, standards developing organisation, or standards-setting organisation) is an organisation whose primary activities are producing technical standards. Typically, a standards body is the organisation that coordinates the process and supports the development of standards and supports their adoption and distribution. Standards bodies may be membership-based organisations, and in this case, it is up to members to write and approve the standards through committees and working groups established for the purpose.

National Standards Bodies do not develop (i.e. write) standards but act as coordination bodies for the broader system of actors. They tend to be independent although some are part of the Government and may operate as public bodies. The NSBs in Europe can support the development of standard at national and international level. Also, they can undertake several activities that are connected to standardisation. For instance, they can respond to the demand for new standards and are responsible for informing the industry about new standards and the withdrawal of old standards. Some NSBs also act as certification bodies by evaluating whether organisations have met requirements set out in a standard.

Countries that are signatories of the World Trade Organisation (WTO) Technical Barriers to Trade (TBT) chapter have a national standards body responsible for the development of national standards and the adoption of new international standards and the publication of standards in their country. In the UK, the British Standards Institution (BSI) is appointed by the UK government to develop and publish British Standards. BSI supports and coordinates UK expertise in making standards, including participation in the development of international standards, the majority of which are also adopted as British Standards. Since 1903, the BSI standards catalogue has grown from less than 100 publications in 1920 to approximately 35,100 publications in 2014. The 1991 Vienna Agreement and the parallel Dresden Agreement in 1996 were signed with the aim of minimising overlap in standards by developing single common standards at international and European level. These agreements resulted in the automatic adoption of many international standards into the BSI catalogue. The international standards organisations, ISO, IEC and ITU, share the standardisation work at the international level:

• The International Organisation for Standardisation (ISO) is the body coordinating the development of formal international standards. ISO standards are developed in almost all industry sectors, except electrotechnical and telecommunications standards (developed by IEC and ITU). ISO is a membership-based organisation and currently has 165 National Members, each of which is the recognised authority on standards in their country. Most of the work of ISO is done by some 2,700 technical committees, subcommittees, and working groups.

• The International Electrotechnical Commission (IEC) is a non-governmental organisation and is the principal body coordinating the development and promulgation of international standards for electrical, electronic and related technologies. IEC is a membership-based organisation, and each member represents a different country. Some 170 technical committees and subcommittees do the IEC standards development work, and each committee is composed of representatives of national committees.

- A third international standards body is the ITU which has been extraordinarily active in telecommunications.

The 2016 US National AI Research and Development Strategic Plan identified ten critical areas for standardisation: software engineering, performance, metrics, safety, usability, interoperability, security, privacy, traceability, and domain-specific standards. At an international level, two bodies are working on AI standards: ISO/IEC JTC 1 Standards Committee on Artificial Intelligence (SC 42) and the working groups of IEEE SA's AI standards series. JTC 1 has published some 3000 standards, addressing everything from programming languages, character renderings, file formats including JPEG, distributed computing architecture, and data security procedures. The second international standards body is the IEEE Standards Association. IEEE is an engineers' professional organisation with a subsidiary Standards Association (SA) whose standards address protocols for products, including Ethernet and WiFi.

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